Connectionist Methods for Data Analysis and Modelling of Human Motion in Sporting Activities

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Attestation of Authorship

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person (except where explicitly defined in the acknowledgements or referenced), nor material which to a substantial extent has been submitted for the award of any other degree or diploma of a university or other institution of higher learning.

Dedication

To my family

Readers Note:

Chapter numeration (in Latin) is omitted from chapter sub-headings (in Arabic). Motivated to reduce the number of digits to reduce the reader's cognitive load, the current chapter is shown in a page header. Some of the tables combine figures with text and some of the figures contain extra elements for intended visibility of information for the multi-discipline audience (e.g. formula with a function graph or internalised data grouping with numbers).
Various algorithm pseudo-code conventions in the literature review may be different from conventions used in this thesis. Supplementary material (e.g. tables, figures and code) in the Appendix adhere to different cross-referencing conventions compared to the rest of the thesis.

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PREAMBLE

"Choosing a PhD topic is quite uncertain task…".

"I agree, but it can be as the same as if you fall in love. Nobody has to tell you anything. You just know it, when it happens." were the words of encouragement, in dear memory to, from my former head of department Prof. John Hughes.

Since my early days, I have enjoyed competing in many sports (swimming, karate, skiing, tennis, etc.) and later in coaching tennis. Later after graduating (University of Maribor), besides working professionally as a software developer, I was competing again and coaching tennis. I have also completed two additional career alternative programmes (University of Ljubljana): one was for coaching tennis and another one was a post-graduate educational curriculum; which have both helped me to teach and appreciate diversity in education from secondary schools in Slovenia (Maritime, Grammar and Italian Grammar) to present teaching days at AUT University in New Zealand.

Experiencing tennis related injury, not being able to play tennis for a long time and going through 'pain barriers' while returning to tennis made me reflect on my game in a way I could not have anticipated while playing at my best. Another motivation to reflect and 'see' the game and surrounding aspects of tennis through different eyes was as a parent-coach. This led me to question: can coaching be supported and advanced via emerging computational methods? and, can implicit coaching knowledge be modelled in a machine?

After implementing successfully my first hypothesis by using a neural network to allow a machine to classify between previously unseen good and poor tennis swings, I have added an additional capability, using evolving computation to facilitate adaptive diagnostic capability.

Following the first few prototypes using collected three-dimensional tennis motion data, I discovered the book "Qualitative Analysis of Human Movement" (Knudson & Morrison, 2002) that provided encouragement as Prof. Hughes had introduced metaphorically. As a result, this thesis is a confluence of my coaching, educational, and other professional experience with the Knudson and Morrison's book and emerging technologies aimed to bridge computational intelligence subdisciplines with kinesiology and related subdisciplines.

ABSTRACT

This research concerns automation of qualitative analysis of human motion in sports, using a novel approach related to assessment and diagnostics, which is required to provide a general user with coaching experience in next generations of motion capture video games or sport coaching software. The research comprises a framework hereinafter referred to as *augmented coaching systems* (ACS) and its critical components.

In contrast to formative assessing of *knowledge of results*, which is based on predefined objective criteria, a qualitative approach to assessing *knowledge of performance* is linked to the questions: (1) Can qualitative assessment be automated?; (2) If so, how can such assessment be communicated from a machine to a human?; and (3) Can qualitative assessment automation be similar to human implicit, multifaceted, empirical, evolving and subjective criteria?

An investigative development approach was used for automating human motion assessment. The assessment of qualitative nature incorporated a mix of objectives – such as subjective, objective, and flexible pre-defined criteria similar to a domain expert or coach. The methods of analysis and *machine learning* techniques included: learning-by-example from expert's data; integrative visualisation/replay functionality for qualitative analysis and *machine learning* modelling; modelling and analysis utilising relatively small and larger unbalanced motion data sets; modular implementation of common-sense descriptive rules mapped to diagnostic outputs; and sub-space modelling and temporal and spatial feature extraction techniques. The introduced ACS framework is generic and it includes a critical analysis applicable to more than one sport discipline. The ACS architecture is modular, extendible and its *machine learning* system supports global, coaching scenario specific, personalised, evolving, and life-long learning.

Using captured motion data sets representing novices towards advanced skill levels in two case studies (golf and tennis), a series of experimental modelling systems integral to ACS were developed for testing and validation using empirical, subjective, and flexible criteria. The results achieved on small and on relatively large unbalanced data sets produced human-intelligible diagnostic outputs in a qualitative fashion. The *machine learning* diagnostic outputs were similar to those produced by visual assessment of a tennis coach (81% ... 99.9%) and to those produced by objective measures from an embedded motion capture system in a golf club, resulting in 89.5 ±2.6%. Flexible assessment criteria were demonstrated by comparing the two different assessments for tennis swing stances that were based on different subjective criteria operating on the same motion data set using the same assessment system. The ACS framework, and developed software components for the next generation of intelligent ACS using subjective and flexible criteria, is novel in the field.

This thesis has demonstrated that qualitative assessment can be automated, that assessment diagnostics can be communicated from a machine to human and that coaching insights as implicit knowledge can be modelled using connectionist and evolving connectionist approaches.

GLOSSARY AND ABBREVIATIONS

2D data: A data set representing two-dimensional spatial information; e.g. 2D video motion data or image sequence.

3D data: A data set representing three-dimensional spatial information; e.g. 3D motion data.

Add-ons, plug-ins: 'Building block' modules, software components or extensions associated with a software design approach to support/enable integration of replaceable and future-available extensions; e.g. a web browser or media player utilising a media codec developed by a third-party.

Assessment: A systematic, formative approach to evaluation of learning that includes collecting information to measure the improvement in learning or to identify areas for improvement against specified criteria in a controlled context or environment. An assessment may be subject to diverse criteria, but may or may not be relevant to the evaluation objective. See also: *Coaching Scenario (CS); Diagnostic elements, diagnostic outputs; Evaluation*.

Augmented Coaching System (ACS): A technology-aided coaching environment to support, for example, a learner's motion assessment and feedback.

Augmented Reality (AR): A technology that enables projection of electronic images over the view of real world objects. "The blend between virtuality and reality" (Dix, Finlay, Abowd, & Beale, 2004, p. 736); e.g. head-up display in aircrafts and modern cars. See also: *Virtual reality; Immersive reality*.

Catastrophic forgetting: A phenomenon in which a connectionist system 'forgets' what it had learned previously after new examples are presented to it.

Chain of errors: A collection of learner-errors and their dynamic relationship. This is typically addressed by coaching cycles and different *coaching scenarios*. See also: *Coaching Scenario (CS)*.

Classification: The result of a connectionist system operation which groups multi-dimensional data patterns into a finite number of categories.

CLI input parameters: A list of one or more values specifying program run-time options, which would change the default command behaviour. See also: *Command Line Interface (CLI)*.

Coaching Rules (CR), heuristics: A common-sense description linked to (motor) learning and skill acquisition.

Coaching Rule Evaluation Module (CREM): An automated machine alternative to diagnostic/atomic element of qualitative analysis. See also: *Diagnostic elements, diagnostic outputs; Motion Heuristic Evaluation Module (MoHEM)*.

Coaching Scenario (CS): A teaching and learning scenario as a sequence of educational activities within a certain context or environment. For example, drill-based training in a controlled environment.

Command Line Interface (CLI): A text or command-based computer interaction paradigm. A program is typically invoked by typing its file name, often followed by a list of 'parameters', followed by the <Enter> or <new line> key. See also: *CLI input parameters*.

Common error (in biomechanics): "Errors that are typically observed in people learning motor skill" (Knudson & Morrison, 2002, p. 219).

Computational Intelligence (CI): A sub-discipline of artificial intelligence (AI). CI is concerned with problem areas to which there are no effective solutions using traditional algorithmic approaches (Duch, 2007; Duch & Mańdziuk, 2007).

Connectionist methods: Modelling and data analysis approaches to support knowledge engineering (KE). These are often associated with early nature-inspired artificial neural networks (ANN) and newer connectionist models developed to simulate cognitive brain functions; e.g. neuro-fuzzy clustering. Connectionist models in general can generalise or operate (on tasks such as pattern recognition, classification and prediction) using noisy, high-dimensional, missing or imprecise data. See also: *Generalisation; Machine Learning (ML)*.

Critical features, static and dynamic features (in biomechanics): A critical feature is a measured state or transition relevant to, for example, a human activity being analysed; Static and dynamic features relate to the observational focus on anatomical or motor sequence. A set of critical features represents measured activity. For example, the maximum knee angle before a vertical jump represents a static observation focus while hip and shoulder turn velocities over time require a dynamic observation focus. See also: *Features (in machine learning).*

Cue: A short instruction to a performer which prompts a more complex/previously-introduced action related to a coaching rule or heuristic. Cue words and cue phrases can be personalised between a learner and a coach.

Data universe: The set of all possible data. Given the evolving nature of many sport disciplines, the available data set is limited to a particular context and therefore is a subset of the *data universe*.

Diagnosis: The identification of human motion errors. The result of judgment based on subjective or objective criteria. Observing and differentiating symptoms as adherence to heuristics or coaching rules. Distinctive characterisation of observed motion to establish optimal feedback and intervention.

Diagnostic elements, diagnostic outputs: Modular diagnostic assessment mapped to a set of heuristics and coaching rules. Automated machine alternative to both assessment and diagnostic evaluation – representing 'atomic' assessment elements of qualitative analysis as diagnostic outputs. See also: *Coaching Rule Evaluation Module (CREM); Motion Heuristic Evaluation Module (MoHEM)*.

Dynamics: Temporal changes within a given context. The context may contain stylistic execution or other temporal pattern dynamics; e.g. 'high-level' strategic game patterns or game intensity changes in time.

Effectiveness of motion sequence: How well a motion technique/pattern, matches the desired goal(s). Typically, the motion sequence is optimised for achieving a prioritised set of goals. For example, in a tennis first-serve return, the effectiveness depends more on timing and safety than the impact speed. See also: *Efficiency of motion sequence*.

Efficiency of motion sequence: "economical use of energy in achieving the goal" (Knudson & Morrison, 2002, p. 83). In biomechanics it is difficult to evaluate and establish how to report the mechanical energy in observed motion. The assessment criteria for a motion technique/pattern may optimised for both *effectiveness* and *efficiency*. See also: *Effectiveness of motion sequence*.

Embedded system: Computerised electronics or a device typically designed for a specific purpose e.g. for motion capture, the embedded system would: be lightweight and small in size, have low-energy consumption, be robust to environment changes, have high processing speed, and suited for both on-line and off-line data communication.

Error component: See: Validation error component.

Evaluation: A component of qualitative analysis where an overall judgment, rating, or opinion is formed. For example, judging a learner's skill and technique for a given context. The notion of quantifying or categorising; for example, how observed motion activity was performed for given purpose. Evaluation can provide a summative estimation to guide further learning. Evaluation outcomes may be based on objective, subjective, or common-sense rules. See also: *Assessment; Diagnostic elements, diagnostic outputs; Coaching Rule Evaluation Module (CREM); Motion Heuristic Evaluation Module (MoHEM)*.

Expert system: A knowledge-based system that can provide similar-to-expert decisions. Expert systems contain captured expert knowledge related to specific tasks or domains.

External synchronisation for visualisation and replay: An interactive functional activation and communication protocol between software components for visualisation and replay; Functionality that enables interoperability with software for modelling and data analysis of human motion. For example, it can be used for coaching, qualitative analysis, and integrated in modelling and data analysis tools.

Feature Extraction Technique (FET): Transformation of raw motion data into a machine learning feature (or variable) set for the purposes of classification or prediction by a connectionist system. Transformed features data may be also referred to as a 'feature space'.

Feature Selection (FS): A selection process aimed to identify a subset of features (or variables) with the most discriminative properties for a classification or prediction model.

Feature space: See: Feature Extraction Technique (FET); Feature Selection (FS).

Features (in machine learning): A set of critical features representing measured activity, transformed into numeric values for the purposes of classification or prediction by a connectionist system. See also: *Critical features (in biomechanics), static and dynamic features (in biomechanics); Feature Extraction Technique (FET).*

Feedback: Communicating information to a learner relating to previous performance. Feedback is commonly intended to guide, improve aspects of human motion related to achieve goal(s), or correct observed motion. Feedback may include intervention.

Generalisation: A desired property of a connectionist system operation (or a machine learning algorithm) enabling autonomous operation; e.g. learning from a finite data set resulting in autonomous pattern recognition of a new (previously unknown, unseen) input data. See also: *Connectionist Methods; Machine Learning (ML); Validation (in CI).*

Heuristics: See: Coaching Rules (CR); Heuristics.

High-level transferable property: High-level transferable property of a system or mental model. The insight or concept that can be captured and transferred between disciplines or transferred into a computing model. For example, layers in a system architecture or computational model; region of impact.

Horizontal market segment technology: Technology applicable to a range of diverse sports or scientific domains. See also: *Vertical market segment technology*.

Immersive Virtual Reality (IVR): A virtual environment where a user is immersed in the environment while interacting. IVR is distinguished from VR in that a participant is 'inside' the environment being simulated. For example indoor golf simulator as opposed to a computer golf game. See also: *Virtual Reality (VR)*.

Inference process, machine inference: A mapping of input to output space through operation of a machine learning system.

Intelligent Tutoring System (ITS): An automated system designed to augment the educational/teaching process of an expert in a specific area of expertise. From a learner's perspective, a part of ITS interactions and communications should be experienced in a personalised fashion to augment the learning process. In general, the term Intelligent Coaching System (ICS) may also be found in the context of ITS.

Inter-rater reliability: The consistency or the agreement of qualitative analysis by a group of people assessing the same subject.

Intra-rater reliability: The consistency of qualitative analysis by the same person e.g. one person producing the same outcome over multiple measurements on the same data. See also: *Reliability; Labelling; Expert data labelling*.

Kinesiology: An integrative, multi-discipline area considering qualitative analysis, biomechanics, coaching, and various other sub-disciplines.

Kinesthetic proprioception: Human-internalised sensing information; Internal vision, 'feel', self-awareness. For example, internalised processing of body parts movement and intuitive interaction with the environment.

Knowledge discovery: Methods of CI and KE may lead to knowledge discovery extracted, for example, machine inference or problem space analysis. See also: *Computational Intelligence (CI); Knowledge Engineering (KE); Problem space*.

Knowledge Engineering (KE): A sub-discipline of artificial intelligence (AI). KE is concerned with the solutions (models, methods, and technologies) to a problem area of an expert's knowledge acquisition; Representing and processing of approximate reasoning, implemented in a machine (or knowledge-based system).

Knowledge of Performance (KP): Subjective knowledge of an activity, for example, of a motion sequence.

Knowledge of performers: Factors that are important for personalisation modelling and internal differentiation associated with qualitative analysis. Personalisation may be linked to skill-level, flexible and subjective assessment, or other forms of similarity grouping.

Knowledge of Results (KR): An objective measure of activity outcomes.

Labelling, expert data labelling: Capturing an expert's decisions by assigning an output category to each data sample. See also: *Intra-rater reliability; Reliability; Supervised learning*.

Learning: A knowledge acquisition or information restructuring process; e.g. 'learning-by-doing' or learning via replay or feedback; Methods associated with machine learning (ML) knowledge acquisition and consolidation of internalised representation of machine knowledge.

Learning rate: The relationship between increasing the training data set and the resulting classification accuracy of a system. Can be conceptualised as 'speed of learning'.

Machine Learning (ML): A sub-discipline of CI or AI. Methods in ML are associated with creating, updating, and recording solutions to common-sense problem areas, or problems difficult to implement in traditional algorithms. Unlike traditional algorithmic solutions, ML involves learning from data. See also: *Knowledge Engineering (KE)*.

Mental model: Individualised perception of how to achieve a goal, often influenced by skill-level. This is generally applicable to movement activity towards achieving a goal or developing a human ability for utilising tools/equipment or to perform abstract tasks. e.g. a tennis swing; basketball hoop shooting. See also: *Coaching Rules (CR); Heuristics; Knowledge of Performance (KP)*.

Metaphor: Explaining the 'unknown' concept/device/entity using terms that are 'known' to a learner or (broader) target audience; e.g. Interface metaphor for a computer 'desktop' where a user may arrange recent or frequently accessed files by analogy to a physical desk.

Motion Heuristic Evaluation Module (MoHEM): An automated machine alternative to diagnostic/atomic element of qualitative analysis. See also: *Diagnostic elements, diagnostic outputs; Coaching Rule Evaluation Module (CREM)*.

Motion sequence: A sequence – for example, of body movements – representing a characteristic pattern or information that can be transformed to a machine learning feature or sample.

Motion sequence design pattern: A solution for static and dynamic machine learning feature extraction techniques. A design pattern that includes motion sequence detection and its separation into functional composition of temporal and spatial processing tasks. An integral component of CREM/MoHEM design. See also: *Software design patterns, design patterns, motion sequence design pattern; Singleton.*

OODA, OODA loop: Cognitive processing stages/phases: Observation, Orientation, Decision, and Action. Applicable to, for example, military training, fire-fighter training, or sporting disciplines.

Orchestration: Adjusting the weights of MoHEM/CREM modules and/or reorganising their collective motion assessment; Evaluation or modelling of a feature space sub-set. See also: *Subspace modelling*.

Output class: A finite set of system output values. See also: *Output labels*.

Output labels: A descriptive list representing output values of a system or output classes, suitable to represent descriptive categories in qualitative assessment of human motion.

Overfitting: An undesired phenomenon in which a machine learning system has learned too closely from training data, which may contain noise and, therefore, cannot generalise well on new data.

Performance: A property of exhibited motion that is optimised to achieve a set of goals. For example, performance may be impeded by conflicting goals and be difficult to assess or quantify. See also: *Effectiveness of motion sequence; Efficiency of motion sequence*.

Plug-in: See: *Add-ons*.

Problem space: A problem space is associated with the notion of data and inherent knowledge via the mapping of the input domain space into the output solution space. The problem space mapping can be a simple formula, a complex relation, or a common-sense descriptive set of rules. Knowledge contained in a problem space may be incomplete or inconsistent. See: *Feature Extraction Technique (FET); Feature Selection (FS); Feature space.*

Qualitative analysis: "The systematic observation and introspective judgment of the quality of human movement for the purpose of providing the most appropriate intervention to improve performance" (Knudson & Morrison, 2002, p. 220). Also: Systematic analysis and judgment of human motion for the purpose of providing appropriate feedback.

Range of correctness for critical features (in biomechanics): A set of effective movement solutions to achieve a particular goal. In biomechanics the critical features are expressed as a human-intelligible measure. The range of correctness as value intervals need to accommodate individual diversities and goal of the movement.

Region of Interest (ROI): A computational phase or method equivalent to cognitive focus of interest; e.g. a ball throw as a characteristic motion event/pattern. Cognitive focus of interest can be either dynamic or static, which relate to temporal and spatial ROI in FET. In machine learning some algorithms also use a term 'Region of Scan' (e.g. voice activation detection) to identify possible presence of ROI. See also: *Feature Extraction Technique (FET)*.

Reliability: Consistency of an expert's subjective classification. See also: Intra-rater reliability; Labelling; Expert data labelling; Supervised learning.

Semi-supervised learning: A machine learning technique utilising both expert-labelled and unlabeled data for training.

Singleton: A program invocation mechanism allowing only one (single) instance to be loaded in memory at any one time. A software design pattern allowing invocation of a single (or max. number of) instance(s) of a process or an application.

Software design patterns, design patterns, motion sequence design pattern: A reusable solution to a common software design problem. Taxonomy of common software design problems and matching solutions. See also: *Motion sequence design pattern; Singleton.*

Subspace modelling: The development and training of individual MoHEM/CREM before *orchestration*. It includes *problem space* partitioning into elements in order to reduce *problem space* and its dimensionality; Modelling of diagnostic elements that may be mapped to coaching rules or heuristics to provide intelligible feedback.

Supervised learning: Training of a system with both input and output data; e.g. input feature set with representative output labels. Output data may be obtained as an objective measure, or captured as subjective empirical data. See also: *Labelling; Expert data labelling*.

SWOT, SWOT analysis: Strengths, Weaknesses Opportunities and Threats. A common strategy used in coaching, talent scouting, team selection, and competitive contexts.

Systematic Observation Strategy (SOS): "A plan to gather all relevant information about a human movement within qualitative analysis." (Knudson & Morrison, 2002, p. 220). SOS is linked to critical analysis and framework for modelling, motion data analysis, and ACS design. See also: *Augmented Coaching System (ACS).*

Taxonomies of critical features: Descriptive lists containing global aspects of analysis of human motion. This assists in a transfer of studies from kinesiology to CI. For example, it may include critical features for skills, fundamental movement patterns (sport/context related), common errors, and common cue lists.

Theory for design and action in information systems (IS): Theory for design and action relates to "how to do something" for development of IS (Gregor, 2006). The associated criteria include utility to a community of users, the novelty of the artefact, and the persuasiveness/validation of claims that it is effective.

Validation (in CI): A testing process to determine how well the system can generalise a solution to previously unseen data. The results are typically compared with the expert (as captured judgments based on subjective measure) or objective measure (e.g. measured data). For example, validation to indicate system operation on transformed selected feature sets. See also: Validation *error component; Validity.*

Validation error component: An error component with cumulative negative effect to validation results of a machine learning system on a particular data set. Some examples are: data set size, distribution and coverage; FET, FS and classifier properties; intra-rater's reliability/consistency; observation/visualisation/replay impairments; random sample selection due to validation process.

Validity: The ability of a coach to correctly identify errors, strengths, weaknesses, critical features, and to conduct specific criterion-referenced observation and analysis. The ability of MoHEM/CREM for specific criterion-based assessment/analysis.

Vertical market segment technology: Technology applicable to a specific sport or user profile. See also: *Horizontal market segment technology*.

Virtual Reality (VR): A state of art multimedia system designed to provide user experience of a synthetic world. A user interacts with a VR system utilising specialised input/output device; e.g. a flight-simulator video games. See also: *Immersive virtual reality; Augmented Reality (AR).*

Note:
Unless quoted and referenced, the glossary terms and abbreviations are applicable to the context of this thesis rather than representing general meaning.

Supplementary CD and reader's note:
The supplementary CD accompanying this thesis includes videos explaining how to use the software with commentary on interdisciplinary concepts and operation evidence.
To improve the reading and the understanding of the thesis, it is suggested you view the video "Personal Tennis Coach" (User Interface Augmented Coaching.mov) that covers the practical application and the thesis terminology, before reading Chapters 2-8.
Appendix E includes the summary of expert tennis coaches' comments after viewing the video, software and tennis data. The supplementary CD provides coaches' permissions to include their names and a summary of their discussion points on the practical use of the software in the thesis.
Golf video (02_Extract_Golf_Features_from_PDF_Scr_capture.m4v) shows the critical evidence of exporting automation of the swing data.

Chapter 1

I. INTRODUCTION

(A snippet of: Raffaello Sanzio. "School of Athens". Retrieved 14-Dec-11, from http://upload.wikimedia.org/wikipedia/commons/9/98/Sanzio_01_Plato_Aristotle.jpg. Reproduced under copyright permissions for educational purposes, www.wikimedia.org).

HEURISTICS ...

Two Greek philosophers discussing the rules that govern someone's skills and expertise; a possibility that an expert might have forgotten some of the rules but can apply and break them when needed; and the role of an educator...

This thesis represents the culmination of a programme of research that set out to understand, model and automate aspects of augmented coaching. Inherent to coaching is the qualitative assessment of human motion, which requires consideration of a set of challenging, largely subjective 'hard-to-quantify' *heuristic* elements. As such, these heuristics are considered as difficult to implement using traditional programming approaches, particularly given the need to be personalised in use and applicable to future, previously unseen motion data.

The demonstrated application of connectionist and evolving methods for the purpose of achieving automated motion assessment equivalent to that performed by a coach provides evidence that human motion can indeed be assessed by a machine. As shown in this thesis through a series of development-experiment cycles, novel outcomes were achieved by applying candidate connectionist approaches via newly constructed software. Novel outcomes started with the demonstration of automated assessments of previously unseen tennis swings (Bacic, 2003a) and concluded with a case study of golf addressing swing accuracy.

1. Background

Compared to widely researched areas of disciplinary convergence such as between computational intelligence (CI) and medicine (e.g. bioinformatics), there is minimal evidence of the application of any of the artificial intelligence (AI) sub-disciplines in coaching or in the general sport kinesiology domain, comprising sport performance, ergonomics, injury prevention and recovery. In kinesiology, the coaching and learning process may be focused on optimising movement for various objectives such as performance, energy efficiency, or safety. As a teaching and learning activity, coaching incorporates aspects of pedagogy and the broader field of education. This thesis is positioned at the confluence of all of these disciplines, first developing then applying advanced *computational intelligence* (CI) methods to the modelling, analysis and diagnosis of human motion in sporting activities.

In the field of education, many advances in teaching and learning automation have been developed over the past two decades[1]. Examples range from automated grading, plagiarism detection and intelligent tutoring systems (ITS) through to the development of advanced content management and information retrieval systems (e.g. www.blackboard.com, http://moodle.org and http://turnitin.com, accessed 31 Mar. 2012). The composite elements of ITS – multidisciplinary design, the underlying information and communication technology (ICT) infrastructure and the application of AI sub-discipline models (Webb, Pazzani, &

[1] Intelligent tutoring systems: applications of AI to education. (2011, 30 Oct.). Retrieved 9 May 2012, from http://aaai.org/AITopics/IntelligentTutoringSystems.

Billsus, 2001; Bacic, 2002, 2003b) – have reached a level of maturity sufficient to inspire investigation of these elements in their application to sport. In sport, one might expect to find comparable *Intelligent Coaching Systems* (ICS) designed to support the personalised learning of a sporting activity; however, there is minimal evidence in the literature of such systems.

In acknowledging the key role of the coach even in a context of automation, rather than ICS the preferred term used in this thesis is *Augmented Coaching Systems* (ACS). Fundamental to ACS and central to this thesis is a requirement for automated qualitative assessment and diagnosis of human motion, linked to the provision of feedback in a similar way to that provided by a human coach.

1.1 Methodology Inspiration: Coaching as an Education Process

The teaching and learning of motor skills so that they can be applied to the performance of a particular sporting task can be viewed as a process of education. In investigating the development of intelligent tutoring systems (Bacic, 2003b) there was evidence of growing use of AI methodologies. This included the application of connectionist methods based on potentially complex patterns, over traditional and rather one-dimensional answer-matching algorithms. In particular, connectionist approaches may be more applicable to the assessment of 'open-nature' learning activities, and so might be used to provide automated support to essay-type marking. In general, the qualitative assessment undertaken in essay-type marking is based on a combination of a 'holistic impression' and qualitative and quantitative adherence to rules or similarity-based criteria or rationale.

An additional perceived benefit of the traditional algorithmic assessment techniques (e.g. mark calculation by comparing multi-choice or numeric results with a model answer) is the simplicity of the reporting of results, as learners are less likely to raise questions, make requests for clarification or challenge the results given that marking is perceived as objective and therefore likely to be fair and accurate. In contrast to this *knowledge of results* mark allocation, qualitative essay assessment is most likely to be subjected to multiple criteria assessed individually and weighted against holistic expectations e.g. novelty, originality. When reporting feedback, it is possible to combine reporting the quantities (i.e. numbers) with a degree of qualitative 'fit' to descriptive categories, indicating possible strengths and weaknesses described in the marking criteria.

This thesis is focused on human motion assessment and so draws on the above concepts and solutions in the context of augmented coaching. The work develops then applies computational methods that can be used for the purpose of qualitative movement assessment. This brings several challenges, including: (1) Providing data for modelling and theory development; (2) Capturing coaching insights, implicit reasoning and empirical knowledge; and (3) Supporting the use of flexible and subjective assessment criteria (e.g. including skill level, coaching goals and possibly experts' disagreement).

Note that it is assumed for the purpose of this thesis that a coach is indeed an expert; while *intra-rater reliability* is expected (i.e. that a coach will be consistent in their assessment) the intent is not to question the sources of a coach's knowledge or generally accepted empirical knowledge.

1.2 Limitations of Existing Sport Performance Technology

In developing and applying elements of an ACS this thesis addresses in part the limitations of existing sport performance technology. In brief (but covered in more detail in Chapter 2) the key constraining issues and limitations of current sport coaching technology (Bačić, 2006a; Bacic, Kasabov, MacDonell, & Pang, 2007) have been:

- No automated qualitative assessment of human motion. Automation of the quantitative assessment of human motion has been achieved to a degree by the processing of biomechanics values computed from motion data;
- No human-like, heuristics-driven assessment inference that can support automated descriptive categorisation of a *motion sequence*, on the basis of the qualitative assessment of motion data;
- Lack of adaptability, that is, no adaptive, evolving or incremental learning;
- Limited degree of automation for motion event indexing and cataloguing;
- Lack of automated reasoning and explanation that would support the understanding of coaching heuristics as cause and consequence;
- Limited general availability. The technology that requires time to learn to enable sports professionals to further refine their skills is typically operated exclusively by sports professionals or experts with specialised scientific backgrounds (e.g. www.vicon.com and www.bts.com, accessed 7. Jan. 2012.). Such technologies are

utilised by horizontal market segments, present in various biomechanics laboratories or similar institutions. Technologies emerging in the general consumer market are designed predominantly for vertical segments or for specific sport disciplines (e.g. Golf ("SmartSwing," 2005; Leadbetter interactive," 2005); and more recent technologically advanced systems such as www.trackman.dk, www.flightscope.com, accessed 7 Jan. 2012 and www.swingprofile.com, accessed 12 Apr. 2012); and

- Limited functionality, performance and availability of independent media viewers to support visualisation and replay for qualitative video analysis and video presentation in coaching.

Each of the limitations just listed represents an opportunity for research and development. This thesis addresses these opportunities.

2. Motivation and Objectives

> ***No great discovery was ever made without a bold guess***
>
> *Sir Isaac Newton*

Before selecting a candidate computational approach, from the theoretical perspective, the following observations of coaching and sporting activity were made:

- Coaches may disagree in their opinions and feedback;
- Assessment of a player's performance may be personalised;
- A successful competitor may not necessarily be a good coach;
- A movement pattern may have one or many goals. Such goals may be conflicting and subject to different priorities, depending on the circumstances;
- Coaching and sporting activities are evolving and an ongoing process. Emphasis may be placed on: game dynamics; individual player progressive achievements; recovery progress; diversity of coaching scenarios; and feedback associated with observed similar motion patterns. Flexible and subjective assessment may depend on a coach's familiarity with the learner, recovery program and other circumstances;

- Related to demographics there: (1) Are many players from novices to intermediate who could benefit from accelerated sport skill acquisition; (2) Are coaches who would prefer to coach at particular levels; and (3) Is an increasingly aging population that could benefit from monitoring and maintaining motor coordination.
- It is difficult to capture a coach's non-deterministic and implicit reasoning, knowledge, heuristics or coaching rules in a computer model.

The motivation for this thesis work came from a variety of sources and multidisciplinary foundations:

- An opportunity to extend the principles of intelligent tutoring to sport coaching;
- A desire to address the limited capabilities of existing sport technology; and
- Recognition of the potential of CI methods and candidate connectionist approaches for motion pattern recognition and adaptive learning from data.

Applying CI to motion data within a learning infrastructure should promote the end-user experiences of motor skill learning and the enhancement of movement technique ideally through an experience that is entertaining and fun. As such, these learning environments – or ACS – are intended to advance coaching, enhance the sporting experience and quality of life.

The intended theoretical contribution is aimed at: (1) Capturing a coach's insights and implicit knowledge into a computer model; and (2) Designing the critical elements for the next generation of intelligent ACS.

As is common in computer science research and in *theory for design and action* in information systems (Nunamaker, Chen, & Purding, 1990-91; Gregor, 2006), the thesis objectives (below) include developing the 'building blocks' of an ACS to form a systematic framework enabling data analysis, modelling, and *knowledge discovery* (KD) regarding sports and related activities. Successful development of these technical elements relies on extensive prior domain analysis – understanding human motion, sport performance, and coaching and learning.

2.1 Primary Objective

The primary objective of this thesis was to develop and evaluate the application of candidate connectionist methods within a systematic framework supporting the analysis and modelling of data drawn from human sporting activities. Unlike traditional computational approaches, candidate connectionist *machine learning* (ML) methods support a problem-solving paradigm based on common-sense rules (heuristics); they can generalise and provide output on low- and high-dimensional data in the presence of noise; and capturing experts' internalised/implicit knowledge e.g. by learning-by-example (*supervised learning*). Common drawbacks to traditional artificial neural networks are: internalised 'black box' operation where machine knowledge is 'encapsulated' inside the model; and lack of general usability to new domains. With the development of neuro-fuzzy and evolving connectionist models that support life-long incremental and adaptive learning as well as rule extraction/insertion, their properties may lead to knowledge discovery from (evolved) machine inference or to capturing machine knowledge as a snapshot in time.

Such an approach is eminently suitable for augmenting the coaching process. Central to this thesis (as depicted in Figure I-1) is the exploration of: (1) What assessment automation tasks can be performed using motion data; and (2) How can motion data be processed to give valid human-like expert feedback in a near real-time scenario (although the latter is outside of the scope of this thesis). The surrounding, wider objectives of the work within which this specific development is situated are: (1) To bridge the interdisciplinary gap between kinesiology and CI; (2) To contribute to the broader application of the sub-fields of CI; and (3) To advance ICT and sport technology in particular. The objectives intentionally include novel synthesis as cross-disciplinary contributions.

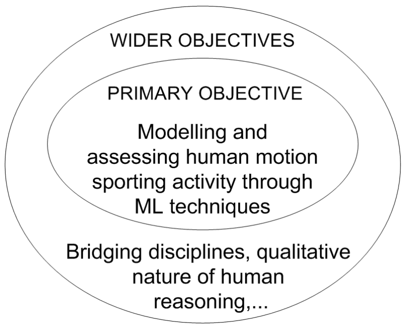

Figure I-1. Depth and breadth of topics in relation to the scope of this thesis.

The specific domain understanding and targeted technical developments required to undertake the two case studies reported here are representative of a more general vision towards a methodology that can leverage future advances in ICT not just in augmented coaching for performance but in other movement-related fields such as injury prevention and rehabilitation. Two supporting case studies utilising captured motion data from tennis and golf activities have been used to demonstrate what can be achieved in automated sports data modelling and analysis.

2.2 Research Questions

The research questions represent the specific goals of this thesis. Fundamental to intelligent movement and skill coaching is the assessment of data (in any form), representing acquired (human) movement, leading to the following key questions:

- *Can the assessment of human motion, as typically performed by a human coach, be automated?*
- *Can human motion be analysed and modelled through the use of connectionist methods according to pre-defined criteria? and*
- *Can qualitative assessment of human motion according to subjective criteria be automated?*

The following sub-questions reflect specific operational goals of an automated assessment system:

- *Can an automated assessment system provide (meaningful) explanation to a human, related to its operation?*
- *Can automated assessment of human motion be achieved given the availability of relatively small data sets? and*
- *Can an automated assessment system be personalised, provide coaching inference rules, operate on pre-defined criteria and evolve its assessment knowledge over time?*

2.3 Scope and Aims

Considering the primary scope of the thesis as being the enhancement of sport performance through automated coaching, the aims also included developing capability for:

- Combining systematic approaches from *machine learning* (ML) data processing with qualitative analysis of human motion;
- Data processing based on flexible and subjective assessment criteria for diverse goals and skill levels; and
- Transferring the high-level system operation aspects or methodological properties:
    - from one sport activity to be applicable (to some degree) to others; and

  - to related domain areas, such as video gaming and digital entertainment.

The boundaries related to data analysis, modelling and processing are:

- Input boundary: The developed methodology should be flexible and reusable – so that it could be adapted to work with a diverse range of motion data sources including future motion acquisition device technology and augmented coaching environments;
- Motion data boundary: Motion data in this thesis must be obtained from human movement. The use of synthetic data is to be avoided (as it is possible to distinguish 'natural' from synthetic movements e.g. evident in animation produced with and without motion capture); and
- Output boundary: The assessment system should produce output data sufficient for assessment interpretation and to support further developments in terms of producing personalised feedback.

3. Multi-discipline Research Design

It is contended in this thesis that it is possible to achieve automated analysis and evaluation of human motion data by combining diverse sources, incorporating the quantitative approaches used in CI and biomechanics along with qualitative approaches used in kinesiology and expert insights. The multi-disciplinary nature of the work developed and evaluated in this thesis means that it leverages a diverse range of sources and research methods (Figure I-2).

The multi-disciplinary methodology utilised here focuses on the qualitative observation of human motion in sporting activity but applies analytical methods from the domain of computer and information science. In summary, this research design:

- Identifies the concepts, characteristics and problems associated with modelling of motion data and the automation of error detection in movement patterns;
- Develops methods, directions and discipline-bridging concepts associated with the automated qualitative analysis of motion data directed towards movement, technique or skill learning; and

- Leverages the domain requirements from sport, along with the capabilities of computer and information science, to implement software components and demonstrate their utility through two case studies.

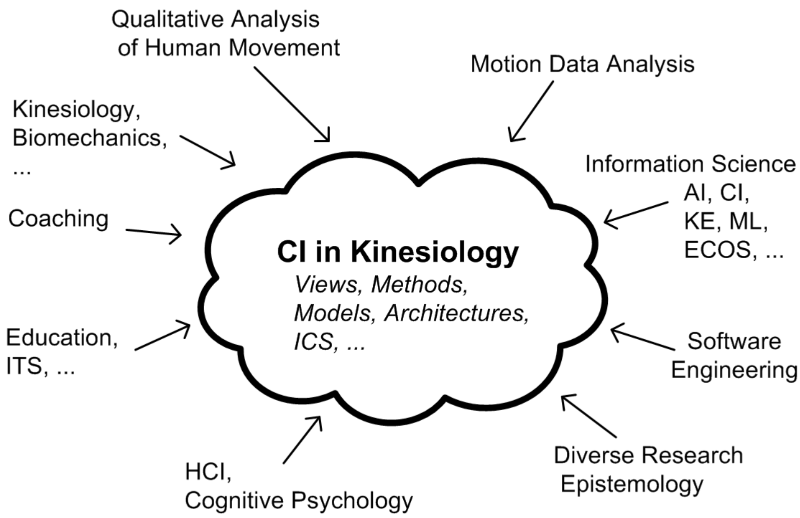

Figure I-2. Inter- and intra-discipline confluence culminating in the embodiment of CI in Kinesiology – a new discipline of research and practice.

3.1 Research Methodology and Rationale

The research design strategy selected here, taking into consideration the diverse disciplines and epistemologies that underpin the work, combines a range of research methods that bring together the areas of kinesiology and ICT. In order to achieve the stated objective of this thesis, it was necessary to combine the qualitative analysis of human motion data with quantitative methodologies predominant in the computing disciplines. Combining research methods led to the use of an integrative model of qualitative analysis (Knudson & Morrison, 2002), data collection, cyclic, flexible and pluralistic research design involving multiple experiments and two embedded case studies. The result was a cyclic approach to research that incorporates reflection at the end of each cycle, aimed at directing and guiding goal-oriented, successive design-build-evaluate cycles as well as informing the context and general theory (as depicted in Figure I-3).

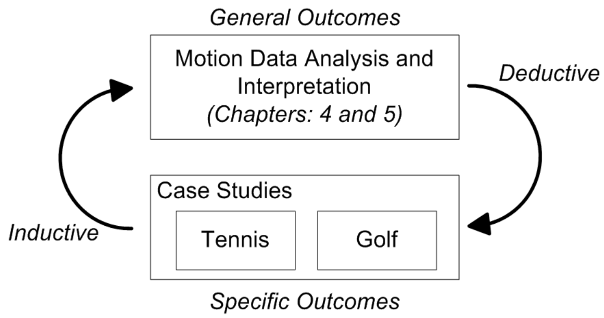

Figure I-3. Research design – combining research approaches in this thesis.

The outcomes support the effectiveness of the research methodology. In particular, the two incrementally designed, embedded case studies collectively cover a range of experimental models and theories that accommodate diverse sources of heuristics and rationales.

3.2 Background on Thesis Research Design

Considering the broad multi-disciplinary context that surrounds it, this thesis is intended to enable applications in augmented coaching but also in other related areas. The approach proposed here leverages the combination of connectionist methods and kinesiology starting from motion data flow, analysis through to processing stages, in a coherent and comprehensive research framework (Chapter 4). A pragmatic and an investigative development approach incorporates a series of experimental modelling systems developed for testing and validation.

3.2.1 Combining Approaches to Research Design

Existing studies (Mingers, 2001; Kampenes, Anda, & Dyba, 2008; Runeson & Höst, 2008) that consider the combining of diverse research paradigms through flexible, multi-cycle, pluralist methodologies are relevant here, given the need to bridge qualitative and quantitative disciplines. In conducting and reporting empirical studies in software engineering and promoting the use of case studies, Runeson & Höst in (2008) identified that: "The analytical research paradigm is not sufficient for investigating complex real life issues, involving humans and their interactions with technology."

This thesis considers the combining of diverse research paradigms and methods with a cyclic research design to be appropriate. The benefits include opportunities to discover a range of inter-related insights from the multiple design experiments, informing the general theories and vice versa (Mingers, 2001; Kampenes et al., 2008; Runeson & Höst, 2008).

3.2.2 Combining General and Specific Outcomes

Combinations of methods embodying different paradigms are developed for specific tasks and their evaluation, applying a cyclic process of inductive/deductive investigation from 'bottom up' feature modelling and informing 'top-down' cross-discipline concepts and vice versa (Figure I-3). Task selection implemented in the two case studies was prioritised by the question: 'What general outcomes can be validated'?

The proposed interaction model (presented in Chapter 5) provided a bridging strategy between hierarchical levels of motion data processing, highlighting the main concepts and their implementations. The case study in Chapter 6, generated practical evidence of connectionist modelling and experimentation on raw 3D motion data to automate qualitative assessment of human motion. The second case study (presented in Chapter 7) generated further practical evidence from the application of the proposed connectionist methodology for data analysis, modelling and interpretation operating on pre-processed feature space originating from motion data.

3.2.3 A Multidisciplinary Focus on Motion Data

Achieving multi-disciplinary synergy of a systematic approach to data processing and analysis necessarily requires expertise from at least the three discipline segments shown in Figure I-4: *knowledge engineering* (KE), kinesiology and software engineering. As highlighted, there is dual primary reliance on KE and kinesiology in this thesis. The software engineering perspective is important here as a means to an end, enabling the development of a viable prototype solution (Chapter 5) and tools for the case studies (Nunamaker et al., 1990-91). This also enables a descriptive research approach (e.g. characterising phenomena in their natural context), to be combined effectively with the computer science research approach (e.g. the development of models, methods, implementation, algorithms and examples of application in the case studies).

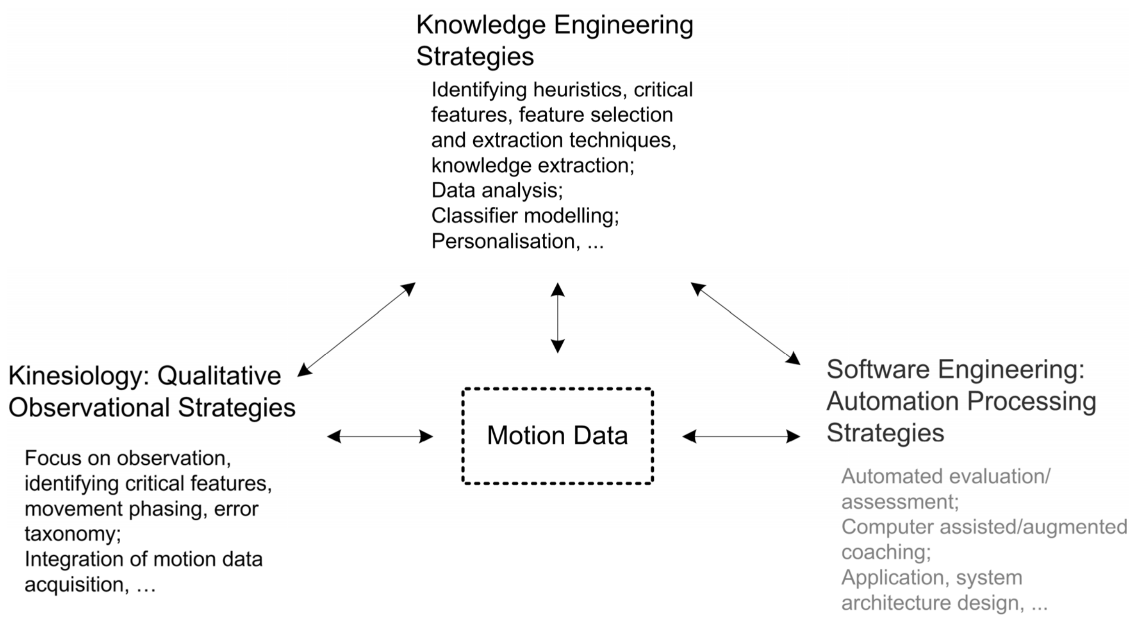

Figure I-4. A multi-disciplinary approach to motion data analysis and processing strategies highlighting the focus on key areas.

3.2.4 Incremental Improvements and Research Design Critique

The use of cyclic and reflective approaches in research design may be more time-consuming compared to more fixed or singular approaches, but with a long term vision in mind they should lead to more generalised outcomes and to the creation of reusable elements that could be further improved as needed. For instance, Chapter 5 describes a 3D viewer (see the video and stand alone executable on the accompanying CD) developed in this thesis work, whose original animated '3D stick-figure' algorithm was initially prototyped in MATLAB™ but was then replaced with the improved equivalent software solution developed for the task of qualitative analysis and *supervised learning* required in Chapter 6.

4. Thesis Structure

The structure of the thesis (Figure I-5) is organised as follows:

- Introducing the motivation and objectives, key ideas and concepts, the principal contributions and outcomes of the thesis, as well as the research design as the general cross-disciplinary research context foundations (**Chapter 1**);

- Foundation background of human motion assessment in sport and critical analysis of methods supporting the research design related to the analysis of human motion linked to the subdisciplines of CI (**Chapter 2**);
- Foundation background of CI, existing connectionist approaches, theories supporting the thesis and informing decisions for the thesis direction (**Chapter 3**);
- General contributions (**Chapters 4-5**) including: (1) Critical analysis of methods supporting the application of CI to kinesiology; (2) Development of the conceptual framework and systematic approach for the augmented coaching system design; (3) Specific developments such as modular design and feature selection and extraction techniques; and (4) General implementation methods, systems architecture, visualisation and system properties to support subjective and flexible assessment concepts;
- Embedded case studies with resulting evidence supporting the general contributions (**Chapters 6 and 7**). Collectively the embedded case studies complement and address mutual limitations extending their common purpose in different sports. As a part of modelling, both chapters include knowledge discovery interpretation specific to sport coaching; and
- Conclusion, critique, opportunities and future work (**Chapter 8**). The novel syntheses as cross-disciplinary contributions are reported in **Appendix A**.

Where appropriate, each chapter contains or revisits elements of the literature review as specific evidence of existing work relevant to the topic being considered in that chapter.

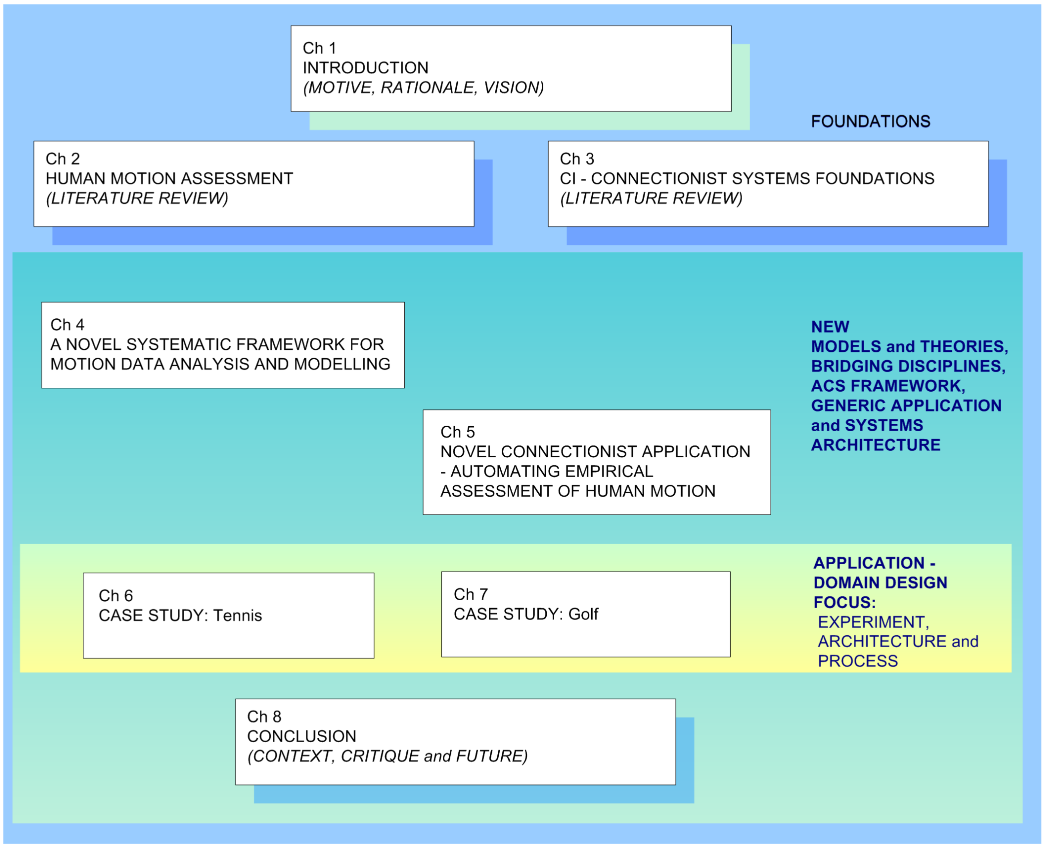

Figure I-5. Thesis structure. All chapters are interlinked as indicated by translucent colour-coded overlapping layers.

5. Contributions

The major novel contributions of this thesis are:

1. Critical analysis and foundations of human motion learning and analysis for the purpose of bridging disciplines (Chapters 2-4).
2. Creation of ACS framework and enabling *human motion modelling and analysis* (HMMA) in sporting activities using connectionist and evolving connectionist methodology as critical components for the next generation of intelligent ACS (Chapters 4-5).
3. A method for quantifying the probability of validation incidents for relatively small or unbalanced motion data sets (Chapter 4).

4. The application of connectionist methods for automated analysis of human motion (both assessment and diagnostic evaluation) based on a mix of objective, subjective and flexible criteria (Chapters 4-7).
5. An implementation of temporal and spatial feature extraction to support the modelling of human motion (Chapters 4-6).
6. An external synchronisation for visualisation and replay. A solution to supporting qualitative analysis and integrative CI modelling of human motion data (Chapter 5).
7. A case study on tennis (Chapter 6). A software system implementation for human motion modelling of tennis activities. The system learns from data and has been validated against expert coach assessments, demonstrating the feasibility of autonomous assessment based on flexible and subjective criteria i.e. by comparing *supervised learning* and modelling of motion data to an expert's assessments.
8. A case study on golf (Chapter 7). A demonstration that proves the feasibility of applying the developed methodology and framework to golf swing activity data analysis, based on objective measures i.e. by comparing predicted data to data measured from embedded electronics in the golf club.

Evidence of the above contributions is structured as follows:

- Experimental evidence, including data analysis and classification results, is summarised in the case studies presented in Chapters 6 and 7; and
- Interdisciplinary contributions – their relevance and significance, and the general insights gained – are presented in Chapter 8 and Appendix A.

5.1 Application of CI to Human Motion Modelling and Analysis

The principal contribution of the thesis is the development of software components capable of automatically assessing human motion and supporting the modelling and analysis of human motion. The CI-based application incorporates:

1. The transformation of critical features for assessing human motion from a biomechanics perspective to features that can be processed by a machine. Given this, the modelling and analysis of data linked to machine features extend beyond simply comparing measured values against predetermined 'expected ranges of values' to multi-dimensional pattern recognition;

2. General systematic framework for CI/machine implementation. Various theoretical and empirical sources (e.g. expert heuristics and insights) are linked to ACS operations and implemented via *machine learning*; and
3. Knowledge discovery from motion data modelling and analysis. The interpretative findings produced could contribute to the further development of a given sport domain.

Investigated methods and techniques of feature selection, rule extraction and the transformation of 3D time-series to n-dimensional data are fundamental to the thesis. Such an approach is similar to that used in the application of CI in other domains (such as speech recognition).

Rather than designing new connectionist models applicable to specific sets of case study data, the intent is to produce a general architecture comprising connectionist approaches within a framework with elements that are applicable to a wider range of sport disciplines.

5.2 Published Work Pertinent to the Thesis

1. Bacic, B. (2002, 24-27 Jun). Constructing intelligent tutoring systems: Design guidelines. *SRCE University Computing Centre, University of Zagreb*. Symposium conducted at the meeting of the 24th International Conference of Information Technology Interfaces - ITI 2002, (pp. 129-134). Cavtat, Croatia.
2. Bacic, B. & Kasabov, N. K. (2002, 30-31 Oct). A general connectionist development environment for sports data indexing and analysis - a case study on tennis. *Knowledge Engineering and Discovery Research Institute (KEDRI), AUT University*. Symposium conducted at the meeting of the Neuro-Computing Colloquium & Workshop - NCC&W'02, (pp. 25-26). Auckland, New Zealand.
3. Bacic, B. (2003a, 20-21 Nov). Automating systems for interpreting biomechanical 3D data using ANN: A case study on tennis. *Knowledge Engineering and Discovery Research Institute (KEDRI), AUT University*. Symposium conducted at the meeting of the 3rd Conference on Neuro-Computing and Evolving Intelligence 2003 - NCEI'03, (pp. 101-102). Auckland, New Zealand.
4. Bacic, B. (2003b, 16-19 Jun). Computer at the University: Opportunities for tailoring automated marking and digital feedback. *SRCE University Computing Centre, University of Zagreb*. Symposium conducted at the meeting of the 25th International Conference of Information Technology Interfaces - ITI 2003, (pp. 31-38). Cavtat, Croatia.
5. Bacic, B. (2004, 25-29 Jul). Towards a neuro fuzzy tennis coach: Automated extraction of the Region of Interest (ROI). *IEEE*. Symposium conducted at the meeting of the International Conference on Fuzzy Systems (FUZZ-IEEE) and International Joint Conference on Neural Networks (IJCNN), (pp. 703-708). Budapest, Hungary.
6. Bacic, B., & Zhang, D. H. (2004, 13-15 Dec). Evaluation of ECOS for the discovery of tennis coaching rules. In N. Kasabov & Z. S. H. Chan (Chair), *Knowledge Engineering and Discovery Research*

Institute (KEDRI), AUT University. Symposium conducted at the meeting of the 4th Conference on Neuro-Computing and Evolving Intelligence - NCEI'04, (pp. 93-94) Auckland, New Zealand.

7. Bačić, B. (2006a, 14-18 Jul). Bridging the gap between biomechanics and artificial intelligence. *Department of Sport Science and Kinesiology, University of Salzburg, Austria*. Symposium conducted at the meeting of the XXIV International Symposium on Biomechanics in Sports, (pp. 371-374). Salzburg, Austria.
8. Bačić, B. (2006b, 13-15 Dec). Using probability in estimating the size of a test data sample. *Knowledge Engineering and Discovery Research Institute (KEDRI), AUT University*. Symposium conducted at the meeting of the 6th International Conference on Hybrid Intelligent Systems (HIS'06) and the 4th International Conference on Neuro Computing and Evolving Intelligence (NCEI'6), (pp. 55-56). Auckland, New Zealand.
9. Bacic, B., Kasabov, N., MacDonell, S., & Pang, S. (2007, 13-16 Nov). Evolving connectionist systems for adaptive sport coaching. *Springer*. Symposium conducted at the meeting of the 14th International Conference, ICONIP 2007, (pp. 416-425). Kitakyushu, Japan.
10. Bacic, B. (2008a). Evolving connectionist systems for adaptive sports coaching. *Neural Information Processing - Letters and Reviews, Vol. 12* (No 1-3, Jan-Mar), 53-62.
11. Bacic, B. (2008b, 23-26 Jun). A novel generic algorithm for cluster split iB-fold cross-validation. *SRCE University Computing Centre, University of Zagreb*. Symposium conducted at the meeting of the 30th International Conference on Information Technology Interfaces – ITI 2008, (pp. 919-924). Cavtat, Croatia. doi:10.1109/ITI.2008.4588534.
12. Bacic, B., Kasabov, N., MacDonell, S., & Pang, S. (2008). Evolving connectionist systems for adaptive sport coaching. In M. Ishikawa, K. Doya, H. Miyamoto & T. Yamakawa (Eds.), *14th International Conference, ICONIP 2007* (pp. 416-425). Kitakyushu, Japan: Springer-Verlag.
13. Bačić, B., & Hume, P. (2012, 2-6 Jul). Augmented video coaching, qualitative analysis and post-production using open source software. *Australian Catholic University (ACU) Melbourne*. Symposium conducted at the meeting of the XXX International Symposium on Biomechanics in Sports, (pp. 363-366). Melbourne, Australia.

Pending Submissions/Acceptance:

14. Bačić, B., & Hume, P. A. (2012). Automated assessment of tennis swing performance: Transfer of qualitative analysis to machine learning and back to coaching feedback. *Sport Biomechanics*.
15. Bačić, B., Kasabov, N., & MacDonell, S. (2012). Evolving connectionist systems for modelling and analysis of human motion. *Evolving Systems*.
16. Bačić, B. (2008, 14-18 Jul). Sport sequence video player for coaches and biomechanists. Symposium conducted at the meeting of the XXVI Conference of International Society of Biomechanics in Sports. (Paper was accepted but could not be presented due to funding issues). Seoul, Korea.

Chapter 2

II. HUMAN MOTION DATA ANALYSIS AND EVALUATION FOR THE PURPOSE OF MOTION ASSESSMENT: A REVIEW OF LITERATURE

This chapter draws on several narrative reviews of prior work focused on background information related to aspects of automation related to human motion assessment. The application of augmented coaching for skill learning is supported by relevant principles from inter-disciplinary fields such as kinesiology, biomechanics, AI, CI and connectionist approaches. With a focus on 'user experience' and 'learning-by-doing', new developments in digital entertainment, virtual reality and gaming are also considered, as they reflect progress in enabling ICT infrastructure that will support advancements in augmented coaching capabilities. It is contended here that advancements in assessment automation will be achieved if elements of qualitative analysis prevalent to coaching can be transferred into a machine and then supported via machine-based methods of analysis.

1. Augmented Coaching and Skill Learning

The first part of this review is focused on identifying the aspects of coaching that can be automated and to what degree. The emphasis is on what has been achieved and what might be done for a majority of learners - sport enthusiasts (novice to intermediate) seeking to use technology-supported sport equipment, rather than specialised, proprietary systems operated exclusively by (and for) specialists. Limited coverage of prior applications/systems indicates a gap, while enabling technological advancements indicate growing opportunities for widely applicable augmented coaching.

1.1 Recent Advances in Technology-Supported Coaching

> ***Coaching is essential to improving as an athlete. Whatever your goal is - a coach will help you see the things you can't - and help you improve so that you don't end up to do the same things over again.***

Andy Murray, Professional Tennis Player, showing his training using Adidas miCoach (www.youtube.com/watch?v=F_QYUq25nhk, accessed 12 Apr. 2012)

Contemporary coaching technology for the consumer market[2] encompasses a wide and growing range of applications for sporting activity, for indoor and outdoor personal use. For example, the worldwide spread of mobile technologies, in addition to digital media display and communication, supports rapid computation and data acquisition. Mobile devices (e.g. mobile-phones, tablets, PDAs) now commonly include accelerometers, gyroscopes, GPS, cameras, and wireless communication for external sensors (Bluetooth, WiFi, sensor arrays). In addition to mobile devices, other prototyping/embedded systems (www.arduino.cc or www.sunspotworld.com, accessed 11-Jan 2012), can also be utilised in assessing and potentially improving an individual's skills.

Another category of augmented coaching technology, but that requires some end-user training, includes general video-based coaching (e.g. SportsCode www.sportstec.com, MotionPro! www.motionprosoftware.com, Dartfish www.dartfish.com/en/index.htm, Quintic Coaching www.quintic.com, timeWARP and siliconCOACH www.siliconcoach.com, accessed 11-Jan 2012), or equivalent combinations/integration of open source alternatives (Bačić & Hume, 2012) (e.g. VirtualDub www.virtualdub.org, Kinovea www.kinovea.org/ and "LongoMatch - The digital coach" http://longomatch.org, accessed 6 Feb. 2012). In addition, domain-specific accessories and gadgets (e.g. a digital video camera and Apple's iPad with SD card adaptor for video exchange) can also be used for indoor/outdoor video-analysis, extending iPad's video capabilities and coaching without the need for a laptop.

[2] For non-expert users.

These technologies typically reflect intended use by one or more different user profiles, such as coaches, sport scientists, elite performers and sport enthusiasts.

Two relatively new systems are TrackMan and FlightScope. TrackMan (www.trackman.dk, accessed 6 Feb. 2012) enables 3D golf ball trajectory and other animated data to be superimposed and compared relative to a target direction indicated in an image (by combining video capture and radar ball direction).

Viewed as an integration of 3D Doppler ball tracking and earlier concepts developed from tennis to cricket and golf, FlightScope (www.flightscope.com, accessed 6 Feb. 2012) systems provide multi-discipline specialised integration of multimedia with real-time 3D data and scoring including operation and integration with a range of portable devices (Apple iOS and Android compatible). While these systems are presently targeted to specialist users, their capabilities may well reach the consumer market in time.

While not directly oriented to video replays, some digital entertainment technologies incorporate virtual environments (e.g. www.allsportsystems.com, www.sportsentertainmentspecialists.com/MultiSportSimulators/index.html, www.bogolf.com and www.virtualgolf.com, accessed 7-Jan 2012). Such digital entertainment technologies together with motion data acquisition games are supporting skill-acquisition through active participation ('learning-by-doing'). Participants are generally motivated by a new experience and the results achieved. Such technologies are evident in the motion acquisition interfaces for popular game consoles (www.nintendo.com/wii, http://us.playstation.com/ps3/playstation-move and www.xbox.com/en-US/kinect, accessed 6-Jan 2012) pioneered by the Nintendo Wii controller, and followed more recently by the Sony PS3 Move controller and further advanced by ubiquitous human motion capture in Microsoft's Kinect.

1.2 Early Augmented Coaching and Personalised Interactive Systems

Two of the initially prominent augmented coaching systems designed for the consumer market were Leadbetter interactive (2005) and SmartSwing (2005), both of which were focused on skill learning in golf. Aspects of automation found in both systems were built on kinesiology, education and biomechanics foundations. Automation of the coaching aspects was achieved either by analysing captured video ("Leadbetter interactive," 2005) or 3D motion data ("SmartSwing," 2005; Nass, 2005). The automated quantitative analysis of captured 3D motion data provided by SmartSwing included computation of *critical features* indicating measured or predicted swing performance aspects e.g. assessment of the segments of a user's swing technique based on expected ranges of values; and variables (also considered in Chapter 7) predicting ball flight. All analysis and swing motion data for individual user(s) were kept permanently in the system. In the absence of accurate 3D data ("Leadbetter interactive," 2005), qualitative analysis of captured video required a human to visually compare and group observation segments of a recorded swing – this enabled a degree of pre-programmed automated matching of identified swing errors with a set of relevant interventions. Grouping by observation was based on the user's perceived similarity to the sample swing segments provided by the system. Utilising data as discrete values from the end-user's visual grouping, the system would generate 'personalised' feedback. Feedback included a set of instructional video clips containing information and interventions in the form of recommended practice drills, pertinent to the preceding qualitative analysis. Golf coaching principles were also evident in a set of introductory and practice drills video clips and DVDs. From an educational perspective, learner performance, progressive achievement and other personalisation aspects were supported by a database containing current and prior activity and associated feedback.

1.3 General Motion Data Assessment Automation

Sporting disciplines may be categorised according to the way performance assessment is conducted, into quantitative (e.g. 100 m sprint), qualitative (e.g. figure skating) or combined categories (e.g. ski jump). The assessment concept in the first category is based on numeric results, while in the second category assessment is based on expert panel assessments. For machine automation, quantitative assessment requires *knowledge of results* (KR) while qualitative assessment requires *knowledge of performance* (KP).

Implementation of automated assessment of KR can be achieved through the application of traditional 'hard-coded rules' in programming approaches, for example:

IF *result* (current_athlete) = *min* (all_athletes) THEN Winner = current_athlete.

Assessment by a machine for KR may be identical to human reasoning using logic rules and as such can be transformed relatively easily into algorithms that are likely to be comprehensible to the human mind. In terms of validation, the existing numeric criteria of KR can be leveraged to ensure consistency (or fairness) of a machine-based assessment.

For automated assessment of KP (also used in coaching), traditional algorithmic approaches are not well suited to 'common sense rules' – *the heuristics* that govern human inference in this context.

1.4 General Challenges in Assessment Automation

Over the past decade, golf excepted, there has been a gap in the application of technologies supporting interactive and augmented coaching for non-specialists i.e. general users who wish to improve their movement patterns specific to sport. While there may be many reasons for this, one asserted here is the difficulty of embedding coaching capabilities in technology.

Arguing the case for the use of *expert systems*, *machine learning* and related disciplines (that include connectionist systems), the early opposing view (Dreyfus, Dreyfus, & Athanasiou, 1986) was that such artificial intelligence could not effectively replace the human mind or intuition. Another rationale (Kecman, 2001) was the slower-than-anticipated development of connectionist systems after the introduction of the early Perceptron model (introduced in Chapter 3). Dreyfus et al. (1986) also argue for the existence of more general obstacles: (1) Existing models (at the time) do not address the issue of evolving perspectives; and (2) It has been known, since the days of early Greek philosophers, that an 'expert' cannot directly articulate the rules from his/her domain that guide his/her decisions. Instead, an expert must regress to view the world as would an advanced beginner in order to perceive then explain some of the rules. From a pedagogical perspective, Dreyfus et al. acknowledged the existence of rules that govern particular skill or domain knowledge and provided a systematic analysis of learning incorporating individual progress from novice to expert over five stages. During that process our inference also evolves from relying on basic rules to problems/solutions in which an expert appears to 'break the rules', or to create what appear to be 'ad-hoc' rules but that are effective all the same.

As noted, human inference and the use of common sense rules – *heuristics* (of Greek origin, for discovery of knowledge or learning by themselves) – typically cannot be transferred into a machine *by traditional algorithmic approaches*. This does not, however, preclude all forms of machine-based support. Computational intelligence (CI) – a sub-discipline of AI – includes amongst its approaches the use of connectionist systems, focusing on: *"studying problems for which there are no effective algorithms"* (Duch, 2007). CI also supports *learning from data* and extraction of machine-generated rules that constitute *machine inference*. For the task of automating the qualitative assessment of human motion, modern mathematical methods from CI include variations of artificial neural networks (ANN) such as evolving connectionist system (ECOS) (Kasabov, 2007a).

Successful applications of CI methods in a variety of domains have led to the development of new cross-disciplinary fields, such as neuro-genetic modelling in bioinformatics (Benuskova & Kasabov, 2007). In education, challenges in assessment automation have been addressed by both traditional algorithmic computation as well as by the use of connectionist systems to provide feedback (Bacic, 2003b). For example, the application of technology in assessment automation, integration and personalisation was found in intelligent tutoring systems (ITS) (Bacic, 2002). At a more abstract level, the synthesis of automation, cyclic assessment and the use of supporting ITS technology in education is summarised in an eight-stage systematic meta-model (Bacic, 2003b). An equivalent general, four-stage systematic approach in coaching (Figure II-2) may therefore serve as a useful framework and starting point to investigate candidate aspects for automation and the development of coaching scenarios.

2. Sport Science: Technique Analysis Perspective

The concept of *technique* appears to be well established in the context of sport science as well as in general sport culture. In contrast, the concepts of *performance* and *technique analysis* – as a systematic qualitative or quantitative method – may be open to different views and further research. For technique analysis, several goals may be identified, but the main justification for its use is to help improve *performance* (Lees, 2001).

A more detailed consideration reveals that performance improvement can be aimed at short-term and long-term (permanent) change via feedback, intervention and practice strategies, leading to targeted and general improvements in a motor skill (Knudson & Morrison, 2002).

The context and concepts (Table II-1) associated with human motion or human movement, are aligned with a hierarchy of terms (Figure II-1), adopted from Knudson & Morrison (1997, p. 71).

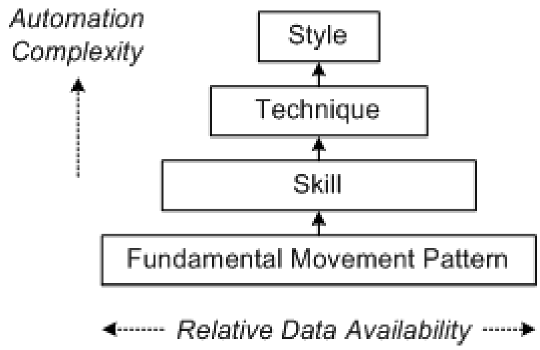

Figure II-1. Hierarchy of concepts relative to data availability and automation complexity of implementation.

More complex concepts (Figure II-1) are expected to require relatively more data in order to enable the implementation of automated support using connectionist approaches.

Table II-1. Introductory terms bridging kinesiology and connectionist views.

Term	Connectionist view or example	Kinesiology view or example
Fundamental movement/motion pattern	Low-level temporal and spatial motion data patterns with (recognisable) contextual meaning.	General purpose movement categories such as walking, throwing, striking, kicking. Fundamental movement patterns may be combined for a specific task.
Skill	Combined movement patterns that could be assessed into descriptive categories.	(Motor) Skill adopted or modified fundamental patterns for specific task or sport e.g. shot put.
Technique	Specific group of patterns assessed under more specific than general criteria.	Selected skills associated with more specific purpose, e.g. banana kick in soccer.
Style	High-level patterns typical for actions related to person or group or task. Difficult to assess given the complexity of hierarchical concepts, causal relation of minor variations influencing performance.	Techniques may be further divided into style variations and personal idiosyncrasies.
Knowledge of Performance (KP)	E.g. discrete category representing assessment or cue. Suitable for computational intelligence (e.g. connectionist) approaches.	Information about movement process, e.g. as cue.

Term	Connectionist view or example	Kinesiology view or example
Knowledge of Result (KR)	Any numeric format representing the outcome. Suitable for traditional computational approaches.	Information of the achieved outcome of the movement e.g. 100m sprint race result.
Deterministic Model	Hierarchical tree structure representing causes and consequence (e.g. desired outcome, skill). There are no weights (or other function) associated with tree branches.	Deterministic model for qualitative analysis (Hay & Reid, 1982; Hay, 1983) of sport skill e.g. distance of a long jump. It is possible to use deterministic models in conjunction with multivariate statistical analysis to indicate strength of associations (Chow & Knudson, 2011).
Critical Features (CF)	Inherent to performance and coaching, critical features need to be assessed or coached in certain way (e.g. sequence, angle) / (e.g. by using cues). CF may be associated with both KP and KR. CF are not to be confused with similar concept of machine learning features.	"Key features of a movement that are necessary for optimal performance" (Knudson & Morrison, 2002, p. 81). The key aspects used in coaching or teaching, helping to focus on good form (e.g. via associated set of coaching cues) or in qualitative analysis of the skill.

The two concepts used for developing automated assessment capability in this thesis are: (1) Swing technique analysis and (2) Motion sequence – event that contains a time sequence of interest (e.g. a swing kinematic chain with its preparation and recovery movement pattern).

3. Integrated Model of Qualitative Analysis

The integrated model of qualitative analysis (Knudson & Morrison, 1997) describes the cyclic nature common to the education process in most kinesiology professions. The teaching activity involving evaluation/diagnosis is described in terms of four major tasks (Figure II-2). A weakness in accomplishing one task, as a consequence, diminishes the effect of subsequent tasks. The model allows flexibility for teaching activities to fit the personal idiosyncrasies of a performer or to a group as needed.

In this thesis, critical features and a selection of observational models of qualitative analysis of human movement are aligned with the multi-discipline perspective as promoted by Knudson & Morrison (2002).

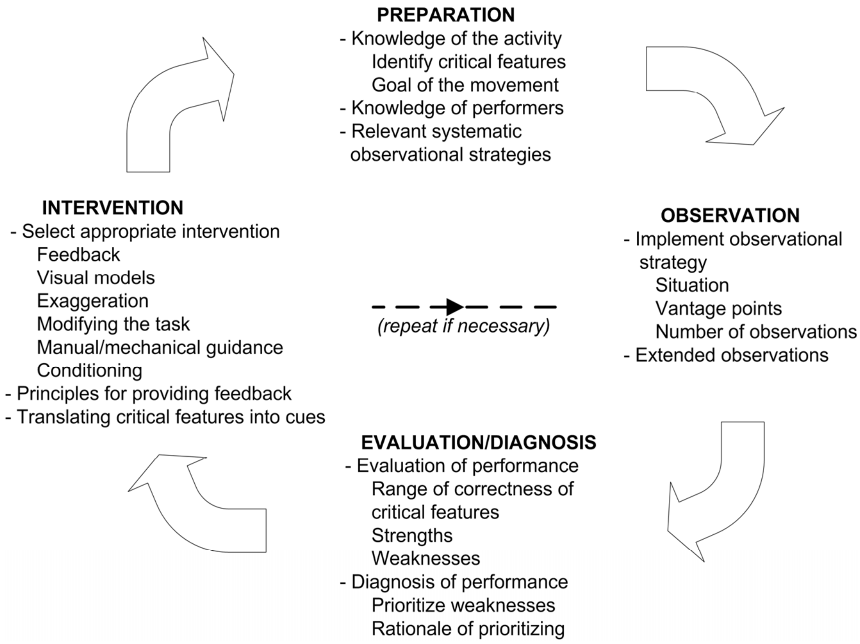

Figure II-2. The comprehensive integrated model of qualitative analysis, reproduced from Knudson & Morrison (1997, p. 27).

3.1 Systematic Observational Strategy and Observational Models

In qualitative analysis of movement patterns, several *systematic observational strategies* (SOS) may be effective, for example: (1) Observational focus on temporal phasing (Figure II-3) (Knudson & Morrison, 2002, p. 156); or (2) Origins of the movements – proximal-to-distal sequencing – from slow-moving to faster-moving segments (Putman, 1991; Sorensen, Zacho, Simonsen, Dyhre-Poulsen, & Klausen, 1996); or (3) Holistic (Gestalt-type) observation from general to specific and rating the importance of critical features (Figure II-4).

3.1.1 Deterministic Model

A systematic approach associated with both qualitative and quantitative information may be evident in a deterministic model: "The deterministic model is a modelling paradigm that determines the relationships between movement outcome measure and the biomechanical factors that produce such a measure (Hay & Reid, 1988)" (Chow & Knudson, 2011). The output of a deterministic model may be represented as a hierarchical tree structure (Figure II-5) showing (desired) outcome and the associated causal movement factors. For example, a desired outcome may be the primary goal of a movement, a performance-related result, or a primary cause of injury.

Temporal and Spatial Model

Body Components	Temporal phasing		
	Preparation	Action	Follow-through
Path of hub	Over base of support	Shift forward to target	Continue movement to target
Body weight	Over base of support	Shift forward to target	On front foot closest to target
Trunk action	Non-throwing side to target	Rotate open to target	Follow arm to target
Head action	Face target	Eyes on target	Eyes on target
Leg action	Apart, weight on back leg	Step to target with closest leg	Bring back leg up to front leg
Arm action	Throwing arm extended back	Bring throwing arm forward	Throwing arm across body
Impact/release		Snap wrist	

Figure II-3. Observational model (Gangstead & Beveridge, 1984) with overarm throwing cues. Adapted from Knudson & Morrison (2002).

Gestalt Model

Dunham Model

Body Orientation:
Preparation:
Feet:
Knees:
Hips:
Trunk:
Shoulders:
Arms:
Hands:
Head:
Execution:
1.
2.
3.
…

OVERHAND THROW

KEYS
Preparation:
Body Orientation: Non-throwing side to target
Feet: Shoulder width apart
Knees: Slightly bent
Hips: Slightly bent
Trunk: Back straight
Shoulders: Non-throwing shoulder to target
Arms: Throwing arm extended back at shoulder height
Hands/Fingers: Three middle fingers on top of ball
Head: Eyes on target

Execution:
1. Step and point with foot closest foot to target
2. Rotate hips then trunk
3. Elbow comes through first, staying high
4. Follow through - bring throwing hand close to floor

Figure II-4. Task sheet observational model (Dunham, 1994) and the example of overhand throw showing keys/cues/critical features and execution sequence (Morrison & Reeve, 1993).

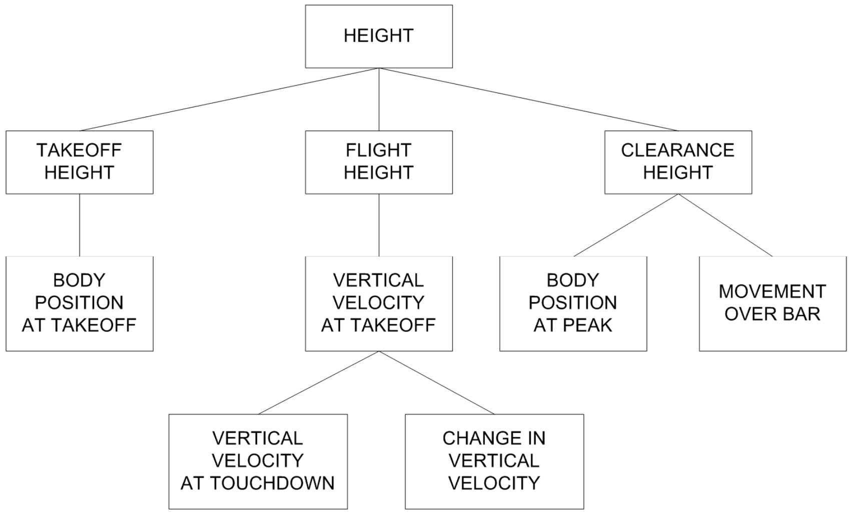

Figure II-5. Basic factors in high jumping (Hay, 1993a, p. 448).

From the pioneering work, which has been attributed to Dr. James G. Hay, over the past three decades the body of research has extended the application of deterministic models in biomechanics analysis predominantly in athletics, swimming and gymnastics (Chow & Knudson, 2011). Chow & Knudson included in their review a concise summary of key findings, statistical approaches, and biomechanical (terminal) factors on subjects performing various desired sporting activities. The general advantages of using deterministic models include:

- Prevention of arbitrary selection of performance variables by focusing on the primary goal and identification of attributing factors;
- Modelling can utilise numeric data as well as qualitative, subjective and discrete categories; and
- Providing information for statistical modelling where there is a need to ensure sufficient data set size relative to the number of variables including the subjects' requirements.

Note that as new findings, equipment advancements or sports governing body restrictions contribute to sports' evolving nature, it is possible to develop more than one deterministic model resulting in the same outcome. For example: Hay (1993b) and Hume, Keogh, & Reid (2005) reported deterministic models of golf drive ball displacement, while the club and ball technology has evolved since the earliest deterministic model.

3.1.2 Evaluation and Diagnosis

A review of concepts surrounding technique analysis (Lees, 2001) presented a view in which technique analysis is an aid to improve performance and therefore is a part of performance analysis. Treated as a more analytical method, however, technique analysis provides a basis for understanding the way in which sport skills are performed and therefore can serve as an aid in the improvement of performance.

The evaluation/diagnosis stage (Figure II-2) includes technique and performance analysis, followed by diagnosis as identification of faults in performance and providing rationale for prioritising weaknesses. Relying on the output from the evaluation/diagnosis stage, the follow up intervention stage includes remediation or intervention to achieve the desired outcome.

3.1.3 Intervention and Feedback

Feedback can include elements of analysis such as knowledge of performance (KP) or knowledge of results (KR). However, feedback should also include qualitative interpretation of such analysis, for example:

> ***… an amateur runner may not know what to do with a system that says "your foot is pronating 32 degrees when it hits the ground". Simpler instructions like "try lifting your knees" could be more helpful.***

Richard Wheater, head of coaching for England Athletics, (Firth, 2011).

The following guidelines (Knudson & Morrison, 2002, p. 132) would be suitable for implementing and reporting movement feedback:

- Don't give too much feedback;
- Be specific;
- Don't delay feedback;
- Keep it positive;
- Provide frequent feedback, especially for novices;

- Use cue words or phrases; and
- Use a variety of approaches.

These guidelines are expected to be applicable in ACS as well as in digital entertainment and future augmented coaching systems.

3.2 Critical Features and Subjective Assessment

The role of *critical features* is one of the important aspects of this thesis that is also well established in coaching and analysis (Morrison & Reeve, 1993; Lees, 2001). For example, for a critical feature it is common that the analyst would establish: the *range of correctness* to establish mapping from analogue scale to ordinal (e.g. 'inadequate', 'within the desirable range', 'excessive') (Knudson, 2000); or different weight shift for different motion patterns; or correct the movement sequence (e.g. the stride before forward swing in softball batting).

It is also known that coaches may disagree (e.g. due to their different backgrounds, familiarity with the learner's background or 'knowledge of performers') and that experts' advice may be conflicting in some circumstances. In real life situations a fear of (re)injury, fatigue or pain may negatively affect aspects of performance of an athlete. For example, an experienced coach may also detect the detrimental impact of fatigue on an athlete's performance – ('*pathomechanics*') investigated as specific predictable resulting movement patterns (Fortenbaugh, Fleisig, & Andrews, 2009). Rather than adhering to defined biomechanical parameters, analysis should therefore also consider possible abstract issues influencing the analysis and intervention (Table II-2).

In addition to the issues and rationale depicted in Table II-2, assessment may also include: biomechanical general/universal movement principles (stretch-shortening cycle of muscle contraction; control of redundant degrees of freedom in the segmental chain); as well as considerations e.g. Bartlett (2007) on critical feature identification within: phase analysis, movement principles, deterministic modelling and ideal/elite template approaches.

For example, coaches of high-performance athletes may attempt to train their players to hit or kick a ball faster, while maintaining an acceptable level of control. As an outcome of biomechanics research that endeavoured to identify factors integral to success in hitting and kicking (Werner, Fleisig, Dillman, & Andrews, 1993; Elliott, 2000), the training of techniques could be optimised, the risk of injury reduced and rehabilitation programmes better structured.

Table II-2. Issues and rationale used to justify desirable technique or the identification of critical features summarised from (Knudson & Morrison, 2002).

Issue	Rationale
1. Safety or risk of injury to the performer.	The safety of a particular action or technique depends on many factors (Pluim & Safran, 2004) such as acute/chronic injury, age, fitness level, muscular imbalance, previous activity, and resting period.
2. Effectiveness in accomplishing the goal of the movement.	Deciding whether a particular form or movement pattern with an associated goal or outcome is effective depends on factors such as weight shift, linear motion components that flatten the arch movement towards the target, and force direction towards the target.
3. Efficiency of goal attainment.	Economical use of energy to achieve the goal. Presence of undesirable redundant movement patterns, often difficult to document.

4. Linking Human Skill Development to Artificial Intelligence: Critical Problem Analysis

Understanding the human ability to learn motor skills and to improve skill development via visualisation, replay, assessment and feedback is a key foundation for envisaging and enabling machine-augmented learning environments (as is the aim in this work). In this thesis the view of performance concepts extends beyond simply achieving measurable changes in movement patterns to being directed towards a specific purpose, reflecting diverse rationales including safety and other qualitative aspects (Table II-2).

4.1 Motor Skill Acquisition and Learning via Assessment

It is commonly noted that, from their early development, children learn movements through trial and error interactions with their environment and through imitation more so than can be observed in adults. Pertinent to this thesis, is that during our development we may also attain the ability to acquire and improve motor skills through exposure to multi-modal inputs such as visual cues, or verbal or written instruction. Our learning might also improve if we develop other mental processing capabilities: *kinesthetic proprioception* as inner vision; grouping characteristic motion events by similarity; or assessing performance with relatively high degrees of accuracy and certainty. In pursuit of motor skill excellence, from novice towards expert levels (Table II-3), learners may also entrust coaches to prioritise goals, assessments and feedback during instruction sessions and may additionally experiment to gain new skills on their own (Table II-4).

4.2 Artificial Intelligence, Human Inference, Skill Level and Modelling Context

Validation of both paradigms for, and implementations of, the ways in which the human mind transforms explicit knowledge into implicit knowledge on the journey to becoming an 'expert' remains a challenge for AI. It also explains why top athletes combine a multitude of information and opinion sources ranging from empirical (e.g. a coach 'said so', with intuitive or logical rationale) to diverse scientific sources (e.g. biomechanics analyses).

Table II-3. Skill acquisition and AI assessment – adopted critique from Dreyfus et al. (1986), "Mind over machine" into a model utilising demonstrable machine learning outcomes.

Skill level	Generalised skill acquisition of a learner, adopted from Dreyfus et al. (1986)	Applicable to skill acquisition, assessment and cross-disciplinary assessment
1. Novice *(Beginner)*	Learning of sub-set or basic rules. No mental model, insights. Can tell *what* to do but not sure *why.*	Minimal set of *Coaching Rules* (CR) assessments. Assessment of KR less important than of KP.
2. Advanced Beginner	Learning more rules. Gaining basics experience. Starting to analyse, rudimentary *mental model* forming. Can execute simple tasks correctly. Can follow task/sequence but cannot apply variations for unexpected situations.	Adding new, or more complex, CR to assessment. More data required, need for personalisation as basic technique evolves. KR assessment and refinement of KP assessment with additional CR.

Skill level	Generalised skill acquisition of a learner, adopted from Dreyfus et al. (1986)	Applicable to skill acquisition, assessment and cross-disciplinary assessment
3. Competence *(Intermediate)*	Wider mental model, gaining more experience. Taking responsibility for advancing and linking KP and KR. Can execute most important movement techniques, tasks and add new ones to existing skill set. Still need to think about the execution and intention.	Training to include *Coaching Scenarios* (CS). KR assessment focus mixed with KP assessment and feedback. Pressure training and partial CS assessments. Situation training as preparation for strategic execution (next level). Future studies in novel learning environments, ICT infrastructures Learning and feedback to include individual learning styles.
4. Proficiency *(Advanced)*	Further gain in experience and wider mental model. Able to plan and execute strategically. On occasions still using rules. Able to transfer knowledge to new circumstances. Elevated concentration on the task and execution.	N/A. Strategic reasoning, Adaptation, Cognitive training aimed to improve response times (e.g. OODA loop).
5. Expert	Broad experience. Automatic and instantaneous execution. Can invent and identify new rules, new phenomena and hypotheses. Can perform with little attention to task. Can perform with deep, sustained concentration 'in-the-zone'. Can communicate or read high-level instruction.	N/A.

Table II-4. Assessment of motor skill, technique and style acquisition and adaptation: Example contexts for different profiles.

Profile	**Open problem question examples**	**Possible user scenarios / goals perspective**
Learner	"How do I identify what can help me to improve my technique"? "Would comparing my and other players' mistakes and optimal performance help me to identify what needs to be improved"?	Investigating/identifying rules and critical features for successful learning outcomes. Achieving goals with minimal or no prior experience or with expert guidance. Satisfactory perceived improvements as validation of a selected practical implementation strategy. Identifying criteria for choosing input information/advice and professional help.
Competitor (individual strategic reasoning)	"Am I losing because my opponent is making fewer mistakes/scoring more winners"? "Am I leading because I score more winners/make fewer mistakes than my opponent"? (McLennan, 2009) "Who plays offensively and who defensively"? "Will I potentially jeopardise the present game outcome now, to gain the future insights and longer term reward"? "Did my game or opponent in the previous match damage my rhythm and technique, or enhanced it – for my next match"? "What should I practice before my next match(es)"?	Strategic game patterns. Optional competitive skill analysis (when needed cognitive activity), outside of execution phase: Ad-hoc SWOT[3] analysis with strategic short-term goal to adapt and win. Rehearsing/recalling in working (short term) memory selected mental images of previously acquired motor skills and techniques. "Game vision" competitive learning characteristics[4] can be exhibited as occasional experimenting (also as "out of the box" strategic thinking) during competition. High-level abstraction and adaptation contexts. E.g. recognising and recalling strong/weak offensive/defensive opponent(s)' patterns/rhythm to combine them with personal abilities/aspects for winning outcome (Musashi, 1643). Targeted (skill, technique or style) training before the next match.
Coach	"Did I identify and diagnose errors and their importance for my student's perceived skill level and profile"? , "What is the best next course of action"?	Optimise goals and provide feedback and intervention.

[3] Strengths, Weaknesses Opportunities and Threats.

[4] "Game vision" – as one of a competitor's properties included in criteria for scouting young talents (Appino, 2010).

Since it is not possible for all people to achieve top proficiency or expertise in a particular recreational skill or sporting domain, it is expected that the majority of participants will seek and require support for personal development in the first one or two distinct skill levels (shown as non-shaded rows in Table II-3). Based on this expectation, the focus in this research is on the application of knowledge engineering to supporting the development of fundamental and explicit knowledge and capabilities embodied in the first two skill levels. The assessment automation for the first two skill levels will also be focused on selected coaching rules relevant to basic stance and performance elements found in basic technique(s). From the AI and CI perspective, it is expected that for higher skill levels (shaded in grey) more data would be required as well as demanding integration of a wider range of input devices.

Topics (introduced partially in Chapter 1) relevant to this thesis are:

1. Similarities and differences between decision boundaries, human inference and *machine learning* inference (Duch & Grudzinski, 2001).
2. Degree of observational model comprehensiveness and available data included in initial prototyping.
3. Degree of comprehensibility of underlying *machine learning* (ML) operation mapped to human reasoning.
4. User acceptance of underlying principles and the opportunities for advancements in augmented coaching environment.

It is also desirable that high-level transferable concepts, models and frameworks would be encapsulated in the form of reusable cross-applicable modules for diverse domains so that the goal of bridging disciplines and developing reusable components based on similar foundations can be achieved.

4.3 Technique Analysis Linked to Artificial Intelligence

One of the essential coaching skills is the ability to analyse technique – to assess and then improve the performance of learners. Contemporary technique analysis and coaching have evolved influenced by established models, concepts and principles such as: Newtonian physics – forces (Zatsiorsky, 2002) and movements (Zatsiorsky, 1998); anatomical (Bartlett, 1996) and cognitive principles (Knudson & Morrison, 2002). As well as leading to multiple discipline information being integrated into coaching, the kinesiology sub-disciplines (motor learning, pedagogy, and biomechanics) have also advanced related fields such as sport equipment manufacturing, ergonomics and rehabilitation. Table II-5 presents a categorised analysis of sports science concepts mapped to aspects of AI, to set out the investigation context o this thesis.

Table II-5. Linking analytical models and concepts from sports science with AI.

Analysis	Link to AI	Analytical model or concept
Qualitative	Investigation and framework on what coaching aspects may be automated.	The comprehensive integrated model of qualitative analysis (Knudson & Morrison, 1997, p. 27)
	Bottom up, spatial and temporal rule based pattern recognition (specific parts of motion) and classification.	Temporal phasing; Observational model (Gangstead & Beveridge, 1984).
	Expert qualitative analysis using video replay – to *machine learning* from data.	Comparison with 'good' and 'bad' performance examples.
	Event indexing automation and region of interest (ROI) concept (see 'Feature Selection and Extraction Techniques', p. 73). Gestalt / holistic connectionist approaches and applications.	Observation focus: Stance, anatomical focus and motor execution sequence in Task sheet model (Dunham, 1994).
Quantitative	Motion data and critical features transformations. Applicable for traditional computational approaches.	Biomechanics calculus, critical features to be quantified within a range of correctness and further computing.
Predictive	Knowledge engineering, connectionist systems applications and future work linking computer graphics, animation, virtual reality and AI.	Mathematical modelling involved in technique analysis (Marshall & Elliott, 1998). Computer simulation and optimisation to seek new solutions to problems in sport (Bartlett, 1999). Testing new ideas and concepts (Nigg, 2006).

In viewing augmented coaching in general as an educational scenario there is also a requirement for a systematic framework in which technology could be linked to observation, motion data acquisition, technique analysis and feedback to learners.

Directions for motion data analysis and computational modelling may also be obtained as integrated information from the domain expert's interviews, biomechanical principles and relevant literature review.

4.4 Utilising Observation Models to Inspire Creation of Heuristics and Coaching Rules

Incremental development of individual modules responsible for specific evaluation or assessment allows experimentation with diverse assessment criteria. This is supported by modular enabling/disabling and weighting of evaluation/assessment module operational properties for a given context and the design of appropriate *coaching rules* (CR) and *coaching scenarios* (CS). After the observation of motion events, an analyst/coach must decide which observational approach is the most appropriate. An analyst may also need to consult relevant literature, or to produce an observational model and focus on execution sub-tasks (see: '*Motor Phase*' in Figure II-7) and/or specific body components (Figure II-6).

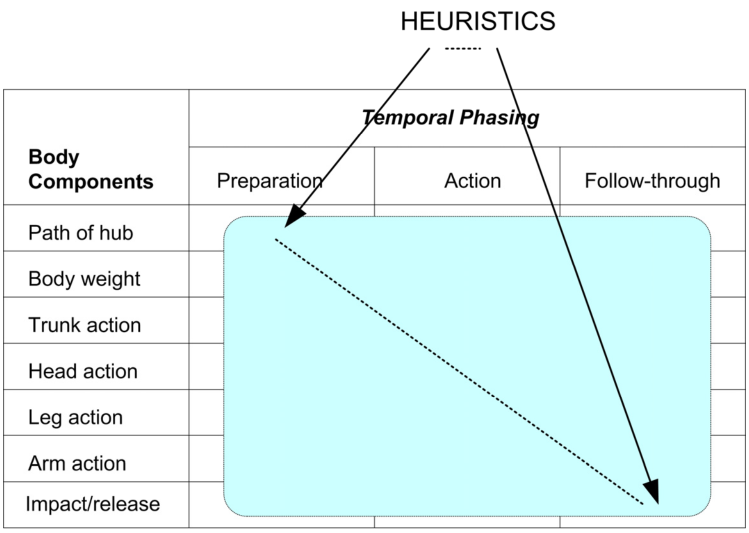

Figure II-6. Individual heuristics on overarm throwing cues. Adapted from the observational model of body part movement through three phases of the movement (Gangstead & Beveridge, 1984).

The proposed approach for connectionist modelling and designing modular assessment system architecture combines modular assessment concepts with a generic coaching process and with qualitative observation models, such as depicted in Figure II-6, Figure II-7 and Figure II-8.

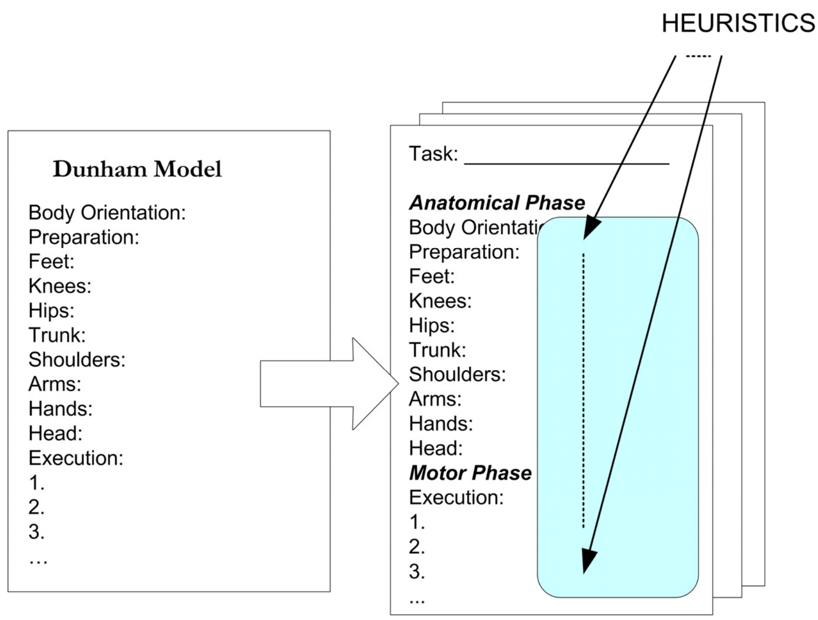

Figure II-7. Task sheet for qualitative analysis (Dunham, 1994). Each task sheet may be associated with the basic movement (fundamental movement pattern) and with a coaching scenario.

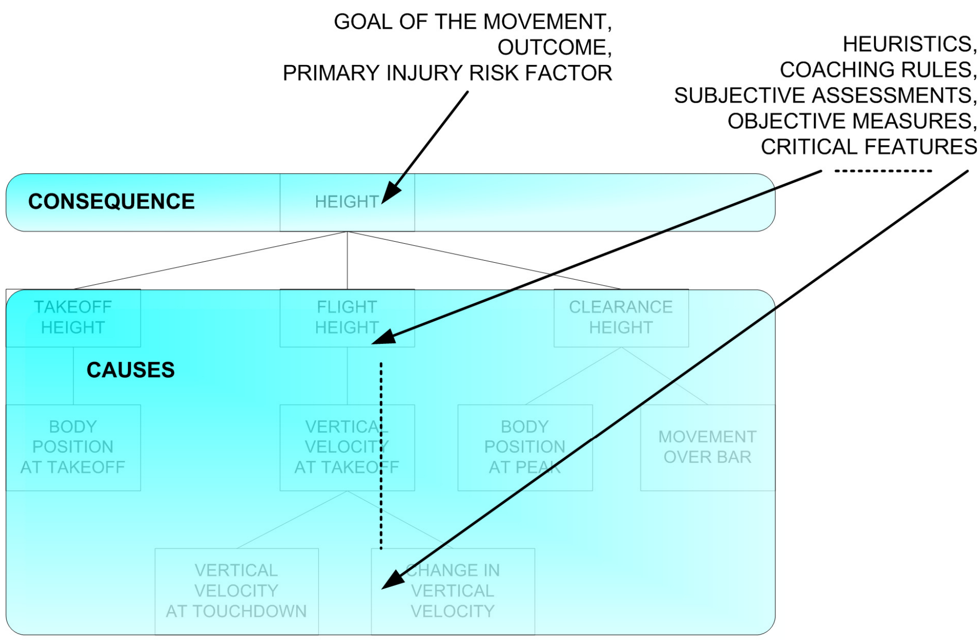

Figure II-8. Deterministic model (Hay, 1993a) associated with goal (consequence) and structure indicating one-to-many relationship with the contributing factors (qualitative and quantitative measure).

The mapping of heuristics from qualitative approaches (Table II-6) to a machine-oriented representation may inspire an identical rule design or a rule variation to be selected for modular implementation.

Table II-6. Summary of observational models as a systematic strategy for collecting heuristics.

Model	Advantages	Disadvantages
Observational model (Gangstead & Beveridge, 1984)	Systematic temporal and spatial mapping, bottom-up view, suitable for transformation from critical features to ML features. Easy to validate each individual processing segment (as an individual cell in the table).	Bottom-up approach, lack of holistic approach (Gestalt – 'big picture').
Task sheet (Dunham, 1994) – observational model	Newer model, closer to human thinking, top-down view, addressing the disadvantages of the above model. Holistic approach inline with (Gestalt principles).	Less direct than the above model, more likely to be susceptible to human bias/interpretation. May not be straight forward to transform to machine processing automaton. Could be more difficult to validate.
Deterministic model (Hay, 1993a) – modelling paradigm	Widely accepted in many sports discipline. Suitable for determining causality, inclusion and redundancy of qualitative and quantitative factors. May utilise both qualitative and quantitative information.	To estimate connection weights using statistical analysis or connectionist approaches, a large data set relative to number of factors (variables) and subjects' requirements may be required. More than one deterministic model for the same goal/outcome may exist.

The presented system design (Chapter 5) supports the capability to have critical features grouped for particular tasks and structured – or *orchestrated* – by their importance (e.g. by assigning weight factors) for learning and assessment automation. In addition to supporting the combination of multiple observational models, Chapter 5 presents a user interface as an interaction model supporting weighting, orchestration and division by assessment purpose of a range of evaluation models (e.g. global, local/group and personal).

Systematic observational strategies and the use of critical features with associated cues provide a link to the 'common-sense' implementation problem area, or "world of heuristics" (Kasabov, 1996, p. 3) specific to knowledge engineering and related disciplines.
The relevance of *systematic observational strategies* and the *deterministic model* in the context of implementing heuristics in a machine and developing augmented coaching systems is evident in the following characteristics:

- Systematic approach to gather heuristics;
- Feature extraction technique design (e.g. static and dynamic observation focus on anatomical or motor sequence);
- Encourage implementation of personalisation aspects of a group or individual performer to supplement the qualitative analysis automation; and
- Design of video replay capability to extend observational power.

Taking into account 3D motion data, the advantage of augmented coaching systems extends to animated viewing of important parts of movements from any virtual camera viewing angle. For augmented coaching application design, modelling of connectionist systems and expert system training, video replay is a prerequisite. Developing replay tools also opens a possibility for software engineering challenges in building reusable libraries, a suitable framework, and tools for gaming, VR and predictive analysis.

5. Chapter Conclusion

The importance of replay technology has been established in qualitative analysis and coaching practice. Since the early automated coaching systems, it was also possible to produce automated feedback and recommended intervention based on: (1) Measured biomechanical critical features; and (2) Human qualitative analysis – as cognitive similarity comparisons from replays into discrete categories analysis (e.g. 'too narrow', 'good', 'too wide'). The other specialised software tools for analysis and feedback visualisation require a coach or a domain expert in qualitative analysis to produce feedback (e.g. as combined video animation overlay) involving laborious and time consuming user interaction.

The need for analysis automation is also similar to a problem area in (qualitative) essay marking (in intelligent tutoring systems design, introduced in Chapter 1). The common challenges include: (1) Design of automated assessment capabilities that can perform in a manner similar to a human expert; and (2) Validation of automated assessment against predefined subjective/descriptive criteria.

Similar to the 'blind review' validation concept, the next chapter introduces *supervised learning* and *cross-validation* methods associated with the foundations of computational intelligence and modelling of nature-inspired connectionist systems (also known as artificial neural networks). Although more difficult to validate than traditional approaches, nature-inspired mathematical models in the form of connectionist systems are considered to provide a valid and acceptable approach to address such 'common sense' problems in a machine.

The identified and addressed problem area of the thesis focuses on automation of qualitative motion data analysis related to identification of faults in performance rather than remediation. Implementing automated diagnosis of faults in performance is a challenge for traditional computing approaches, whereas connectionist approaches have been used for solving diverse real world commonsense problems similar to this.

As an opportunity to investigate machine-generated inference, and incremental/evolving machine learning, the next chapter also includes some of the more recent connectionist systems designs (evolving clustering, hybrid neural network models with fuzzy approaches) that represent their internalised knowledge as a set of rules constituting the assessment criteria.

Chapter 3

III. COMPUTATIONAL INTELLIGENCE FOUNDATION

Complementing the prior chapter's review of sporting technology and kinesiology, this chapter draws on connectionist and evolving connectionist approaches and the application of computational intelligence in the domain of augmented coaching.

1. Computational Intelligence and Knowledge Engineering: A Connectionist Systems Perspective

Advancing the field of neural networks and fuzzy systems (Dreyfus et al., 1986; DARPA, 1988; Yoon, 1991; Yamakawa, 1992; Zadeh, 1994; Arbib, 1995; Bishop, 1995; Mitchell, 1997; Yamakawa & Uchino, 1997) (Figure III-1), with the evolving connectionist systems paradigm, (Kasabov, 2002), Kasabov had introduced the opportunities as: *"the enormity of scientific problems"* and *"the acute need for efficient computer models and systems"*. Addressing these opportunities required new computational paradigms, and various authors have provided insights into what constitutes CI by identifying interdisciplinary gaps, scientific disciplines, various problem areas and methods, from the most recent to some more than 40 years old[5] (Duch, 2007).

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[5] As in pattern recognition, operations research and statistics

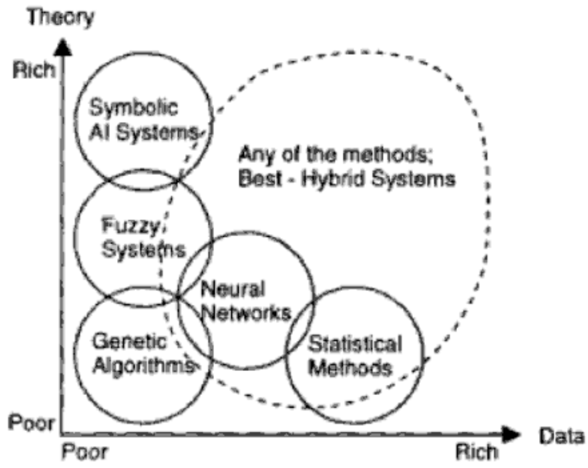


Figure III-1. "Usability of different methods for knowledge engineering and problem-solving depending on availability of data and expertise (theories) on a problem" (Kasabov, 1996, p. 67).

In evaluating the feasibility of a connectionist system or connectionist methods to solve a particular problem, a designer would generally consider: available (raw) data, context and the theories within the context; and possible implementation method(s) (Figure III-1).

Terminology in the field of computational intelligence (CI) and its sub-disciplines (soft computing, machine learning) is exceptionally diverse and often similar concepts are variously named because of its broad-based origins (in, for instance, approximation theory, nonlinear optimisation, statistics), (Kecman, 2001). Given that this thesis sits at the confluence of several disciplines, synonyms and cross-discipline disambiguation are addressed and acknowledged here within relevant contexts.

1.1 Data Processing Concepts

A starting point for the consideration of some of the relevant inter-disciplinary concepts is provided in Table III-1, which introduces a mapping of selected terms used in this thesis across the fields of connectionism and kinesiology.

Connectionist models acquire their *knowledge* through the process of *learning*, changing their internal structure or properties such as connection weights (Kasabov, 1996). Based on the principle that internal structure and connection weights are numerical information associated with operation of a connectionist model, it is difficult to present such numerical machine knowledge to a human in a readily usable form. This challenge is addressed with the concept of rule insertion and extraction from a fuzzy neural network.

Table III-1. Introductory terms bridging connectionist systems and kinesiology.

Term	Connectionist view	Kinesiology example
Information	Structured numeric data with contextual meaning.	Stick figure marker position multiple time series, angular velocity, ground resistant force vector.
Knowledge	High-level structured general information on internal connectionist system representation.	Internalised (machine or mental) rules to evaluate observed motion event as being 'excessive', 'within the desirable range' or 'inadequate'.
Heuristics	'Loosely' explained common-sense rules that cannot be directly translated into a computer program.	A set of common sense coaching rules, enabling a coach to explain assessment of recognised motion event. A learner is able to rationalise on performed basic techniques or acquire new ones.
Inference	Matching of current data sample to output as a result of training with past data	Conclusions (of a machine or mind) based on observed evidence, domain expertise and reasoning.
Generalisation	Best possible matching of previously not matched data, as a result of training with past data	Expert's (competitor or coach) ability to assess a new player with individual idiosyncrasies. Facilitated (or impeded) transfer from one sport discipline to another.

A second challenge in the context of qualitative assessment of human motion is the integration of connectionist systems to implement a set of heuristic and human-like (domain specific) reasoning into a system design, whose evaluation of feasibility is dependent on availability of data (Figure III-1). A third challenge is to achieve system usability with inference similar to that of a human that would generalise well on future data and yet be intelligible to a human mind.

From the machine learning (ML) perspective (a sub-discipline of CI), all introduced concepts and problem/solution computational contexts must be presented as numeric data (Kasabov, 1996). Such a problem-solving paradigm (Figure III-2) can be viewed as a mapping of domain space D into solution space S *(Kasabov, 1996).* A function describing a system operation of such a mapping is called an *objective function* (or *goal function*). The domain space D holds all possible combinations of values of the input variables and the solution space S holds all possible combinations of values of the output variables. Heuristic rules in a knowledge base can be viewed as a 'simplified' model of an original, real world model or as 'patches' – a collection of input vectors mapped to a collection of output vectors, covering (a subset of) the solution space (Figure III-2).

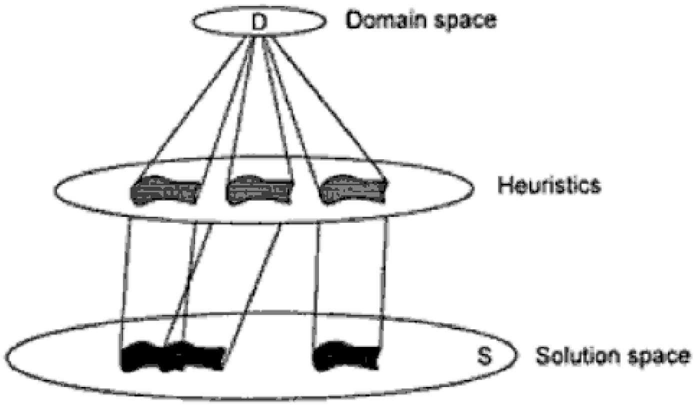


Figure III-2. "Heuristics as a means of obtaining restricted projections from the domain space (D) into the solution space (S)." (Kasabov, 1996, p. 5).

Data analysis should consider information about data set size such as the number of data samples and the dimensionality of the feature space plus the number of output classes. The importance of data analysis concepts in the context of this thesis relates to *modelling* and *model validation*.

1.2 Modelling, Model Validation and Supervised Learning

Modelling in this thesis is described as finding a general solution in the form of a connectionist system implementation (or otherwise module, structure, rules, algorithms or formulas). *General solution* refers to a property of connectionist systems to generalise based on learning from available data – being a *problem space* (Kasabov, 2007a) of a model – towards autonomous operation on previously unavailable samples from the *data universe*.

Model validation, based on supervised learning (such as learning from an expert's decision on available data), in this thesis (Chapters 6 and 7) includes: split-sample ('holdout' method) and cross-validations technique such as leave one out (LOO) and k-fold (Table III-2). Acquired or available 'raw' data typically is analysed, transferred, represented within a particular context before and after being processed by a connectionist system. Model validation indicates processing accuracy relative to the available data – taking into consideration how well the available data represents the *data universe* (Figure III-2).

Table III-2. Model validation decisions.

Validation	Pros	Cons	Decision
Train-test holdout	Larger portion of randomly selected test samples ensures overfitting prevention. Expected better general indication for accuracy than LOO.	Not recommended for small data set due to leaving insufficient training data set portion and possibility of random incidents, where training potion may not be representative.	To be used on mid to large data sets.
k-fold cross-validation	Compromise between holdout and LOO.	May result in incidents (see above), e.g. that some folds could have only one (majority) class for testing.	To be used in mid to large data sets.
LOO cross-validation	Maximising train portion with small data sets. No random incidents, where an entire cluster being randomly selected for testing.	May lead to model overfitting. Computationally intensive and time consuming. Not practical for large data sets.	To be used on small data sets.

Linked to validation of the experiments in this thesis, standard approaches of model validation such as those shown in Table III-2 provide quantification of classification accuracy on subsets of the *data universe* utilising *supervised learning* technique(s). For cases where *supervised learning* involves human/domain expert data, the classification accuracy is a measure of agreement between human and machine (model) classification (assessment) based on available data. The data size property is considered small, for example, if there is either a small number of samples available for modelling or if the problem dimensionality (number of features and output categories) is large relative to the number of available data samples. For relatively small data sets modelling research should consider the selection of appropriate data analysis and model validation methods e.g. clustering, overlapping investigation, data density related to output categories and other techniques to estimate how well data may represent the *data universe* and where possible an indication of model overfitting. During the modelling activities it is possible that research activities (knowledge engineering) could lead to *knowledge discovery* – advancing the state of the art of a particular domain.

2. Motion Data Analysis: A Connectionist Systems Perspective

As introduced, motion data must be presented in a numerical data form to a connectionist system. The origin of acquired 'raw' motion data may be diverse in nature and for a connectionist model various transformation techniques may need to be included in modelling. Different types of numeric data representing measured human activity may be obtained from video, sound or any analogue or digital source. Sources include: accelerometers, electromyography (EMG), retro-reflective 3D motion acquisition systems and various other devices (Bartlett, 1996; Winter, 2009).

Data properties of particular relevance to this thesis include accuracy, sampling frequency and relative cost of acquisition given the intended application scope (being augmented interactive coaching infrastructure feasibility).

2.1 Machine Learning: Features and Output Classes

Depending on their form, different types of acquired motion data may need to be transformed in order to be represented in a machine learning system. The process shown in Figure III-3 represents general connectionist system modelling, starting with data transformation from, for example, 3D multi-time series of body positions to a connectionist system for *classification* purposes. Figure III-3 represents: (1) Time-series transformation to features; (2) Feature selection; (3) Further feature transformation and (4) Feature pattern matching – data classification into representative groups i.e. *output classes*.

Data transformation resulting in reduced dimensionality of data/feature space is referred to as *feature extraction*, while an investigative/modelling method focusing on feature extraction is referred to as a *feature extraction technique* (FET). A machine learning data format suitable for discrete output classes may be given as successive integer numbers e.g. {0, 1, 2 … n}. An alternative approach commonly used in documenting *output class* and discrete categories, closer to human reasoning, utilises the synonym *output labels* e.g. {'excellent', 'average', 'bad'}.

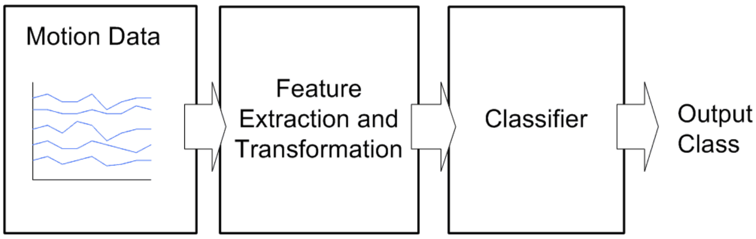


Figure III-3. Transforming motion data (as multiple time series) to features for machine classification.

If needed for classification, feature data may be further scaled within a new interval [min, max]. Such data transformation from the original scale to another, predefined scale is referred to as *normalisation*. For example, formula (III-1) shows linear normalisation of current value *v*, into scale e.g. $x_{min}=0$, $x_{max}=1$ (Kasabov, 2002, p. 299).

$$v_{norm} = \frac{v - x_{\min}}{x_{\max} - x_{\min}}; x \in [x_{\min}, x_{\max}] \qquad \text{(III-1)}$$

2.1.1 Feature Selection and Extraction Techniques

As stated above, modelling in this thesis is considered to be finding a general solution in the form of a connectionist system implementation (or otherwise module, structure, rules, algorithms or formulas). Pertinent to this thesis, in addition to an overview of common feature extraction techniques, Kasabov (1996, p. 89), provided three contextual insights: (1) A perspective: "Extracting features is an ability of the human brain for abstraction" which relates to linking qualitative analytical models and concepts (Table II-5) with feature selection and transformation for machine learning; (2) Topics of pattern recognition, which may be formulated as classification tasks i.e. associating a new input pattern with the closest similar pattern(s). Similar to motion data and classification, patterns can be spatial (e.g. images, signatures and various signs) and temporal (e.g. voice activation detection, speech recognition, heart and brain signals); (3) In general for spatial and temporal signals, it is common that temporal transformation methods are applied first, and spatial pattern recognition is used afterward. This insight is also linked to analytical models in kinesiology (e.g. Figure II-3 and Figure II-4), where the concept of temporal phasing and related investigative directions maps to similar temporal and spatial problem areas introduced further in this thesis.

In this thesis patterns can also exhibit combined temporal and spatial properties (e.g. video, motion data). Complementing techniques for feature extraction may utilise a 'sliding window' approach e.g. for energy detection before feature selection and extraction used in voice activity detection (Singh & Boland, 2007) and region of interest (ROI) detection for temporal or spatial feature analysis (e.g. video and image pattern recognition in fMRI, surveillance, biometrics, tracking systems, vehicle registration plate acquisitions).

Recording expert's assessment categories of observed (input) patterns is referred to as *expert labelling* (human decision making process output). Combining such input and output data is used for training (also known as *supervised learning*) and validation of a connectionist system operation. The next challenge is in identifying and transforming motion data into machine features that discriminate well-represented motion data patterns into their respective classes. For example, before classifier modelling, analytical tasks would involve: (1) Identifying a set of heuristics (e.g. expressed in cues, critical features, observation models in sports technique analysis); (2) Data acquisition; (3) Visual grouping of human motion patterns into categories such as 'good' or 'bad' (e.g. by expert's observation/replay and analysis); and (4) Feature analysis, feature selection and feature extraction techniques.

From a knowledge engineering discipline perspective, for each of the modelling steps shown in Table III-3 a form of data analysis can provide useful insights to achieve desired outcomes and generate new findings applicable to real world problems, based on machine learning.

Table III-3. General challenges involved in modelling and prototyping.

Key step	Desired outcome
1. Data collection.	Sufficient variations and number of data samples to test a set of heuristics or coaching rules. Representative data set ensuring generalisation. High accuracy, sampling rate and low noise.
2. Feature selection and feature extraction techniques.	Small number of features (feature space dimensionality relative to available input data) that discriminate well (low correlation) input to output data.
3. Modelling a classifier.	High classification accuracy relative to human expert. Low overfitting and good generalisation to future data.

Data analysis may include data visualisation tools (2D and 3D graphs) for visual pattern recognition, density distribution (e.g. identifying balanced and imbalanced data distribution), and other existing statistical visualisation tools for clustering, correlation and variable space transformations. For example, clustering techniques such as *k-means* (MacQueen, 1967), with the number of clusters predefined before the start of computation or more recent evolving clustering (Figure III-8), introduced further (in ECF, p. 82). Statistical methods for feature analysis and transformation include: correlation ranking/filtering methods such as signal-to-noise-ratio (SNR); feature transformation (from original variable space into a new one) and variable ranking visualisation tools such as *principal component analysis* (PCA) and *linear discriminant analysis* (LDA). SNR, PCA and LDA are included in the knowledge discovery tool "Neuro-computing environment for evolving intelligence" (NeuCom), (Song et al., 2008) and documented in (Kasabov, 2007a).

2.1.2 Traditional Filtering Methods

Traditional filtering methods are: *t*-test, correlation, and ranking based on *signal to noise ratio* (Kasabov, 2007a, p. 16). For example:

- Pearson correlation formula (Kasabov, 2007a, p. 16)

$$Corr = \frac{\sum_{i=1}^{n}(x_i - Mx)\cdot(y_i - My)}{(n-1)\cdot\sigma_x\cdot\sigma_y} \tag{III-2}$$

Where:

x_i $(i=1,2,\ldots,d_1)$	… input (independent) variables
y_j $(j=1,2,\ldots,d_2)$	… output (dependent) variables
Mx	… mean of the variable x for class 1
My	… mean of this variable y for class 2
σ	… standard deviation.

- Signal to noise ratio (SNR) formula

$$SNRx = \frac{abs(Mx - My)}{\sigma_x + \sigma_y} \tag{III-3}$$

A hybrid approach utilised in (Goh, Song, & Kasabov, 2004) for feature selection and ranking combined SNR (III-3) and Pearson's correlation (III-2) formulae. Although similar (in calculating a feature's mean and the standard deviation), the reported computation time of calculating the Pearson correlation matrix increases exponentially with the size of the data set. The other reported advantage for cases where the number of variables can be reduced significantly is that the SNR method is more capable (than Pearson's correlation) of detecting and ranking a smaller number of significant variables. Goh et al. (2004) found that with an increased number of variables, or in the presence of noise, the mean and variance of the rest of the variables of other classes are dependent on the data dispersion and the number of variables – which affects the SNR ranking of the significant variables due to the general increase of noise in the data. Methods for variable ranking and feature space reduction are important for this thesis given that machine feature space reduction may improve classification results on available data sets. Methods such as SVM and other traditional connectionist systems (Table III-4) can be utilized for comparison with modern evolving connectionist approaches. The concept of a 'filtering method' has significance to this thesis for the circumstances in which a designer needs to optimize problem space reduction with reasonably acceptable classification accuracy for the available data set size and data precision requirements/constraints (in terms of sampling frequency and resolution).

2.2 Connectionist Systems

Connectionist systems (COS), commonly referred to as artificial neural networks (ANN) can be described as nature-inspired, highly interconnected parallel processing structures (Figure III-4) for prediction (approximation) and categorisation (classification) tasks.

A generic artificial neuron as a processing unit has the following parameters:

- Input connections ($x_1, \ldots, x_n$) with assigned weights ($w_1, \ldots, w_n$). The input domain is usually scaled using normalisation techniques e.g. linear normalisation (III-1);
- Processing function, which is a functional composition of the input and activation functions. The input function is usually assumed to be equal to linear combination $f(x,w)=\sum_{i=1}^{n} x_i w_i$ of vectors X and W, while the activation function $a = g$ that calculates the activation level of the neuron may be linear or non-linear; and
- Output function $y = g(f)$ range is therefore limited to range of activation function $y = a$, while the input function range, is expected to be a subset of activation function domain.

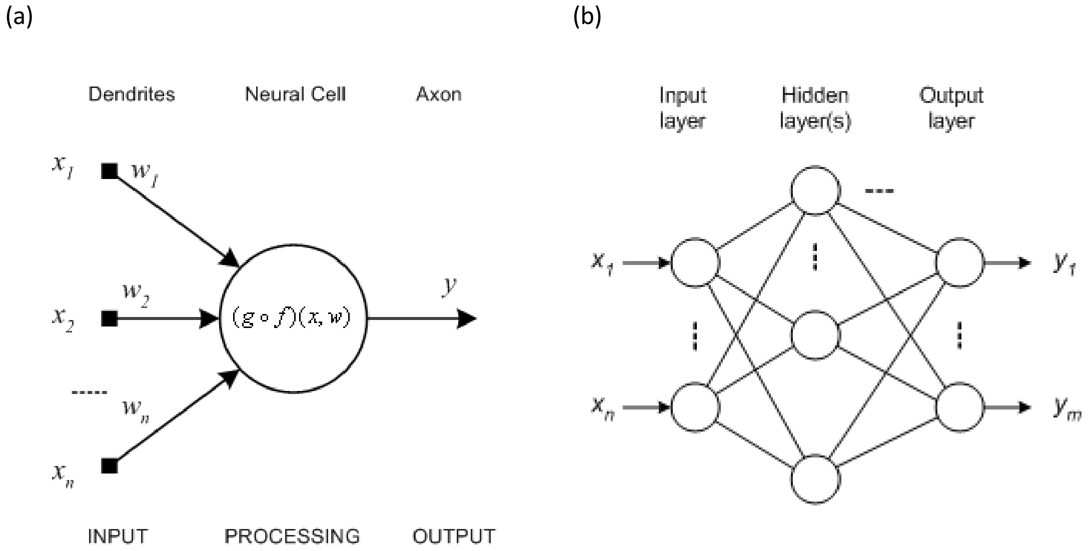
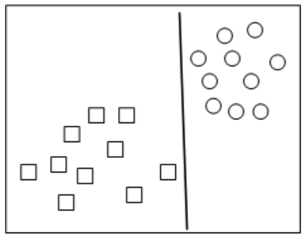
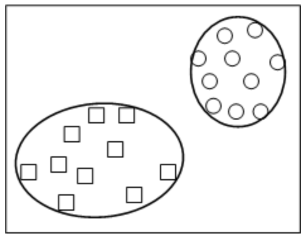
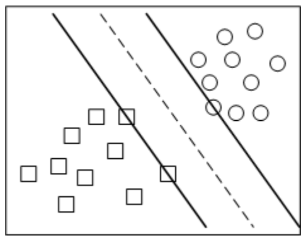


Figure III-4. A nature-inspired generic model representing (a) artificial neuron as a processing unit; and (b) highly interconnected parallel processing structures.

The first working model of ANN, named the 'Perceptron' (Rosenblatt, 1958), was introduced over a decade after the introduction of the first mathematical model of an artificial neuron (McCulloch & Pitts, 1943). The Perceptron learning (training) algorithm worked well on linearly separable data. For real world tasks, where data may overlap or not be linearly separable, it was not effective. Three decades later, after a relatively slow start in the field, two new ANNs were introduced: the multi-layer Perceptron (MLP) with *error backpropagation* learning algorithm (Rumelhart, Hinton, & Williams, 1986; Rumelhart & McClelland, 1986) and the radial basis function (RBF) with a single intermediate hidden layer structure (Powell, 1985, 1987b, 1987a). The new advancements and applications of RBF on real world tasks (Broomhead & Lowe, 1988b, 1988a; Moody & Darken, 1989; Renals & Rohwer, 1989; Mak, Allen, & Sexton, 1994) generated greater popularity for ANNs in general from that point in time. Another popular ANN is the support vector machine (SVM), (Vapnik, 1998, 1999), based on earlier theoretical studies (Vapnik & Chervonenkis, 1971).

Table III-4. Conceptual comparisons of early ANN approaches, summarised from (Bishop, 1995; Kasabov, 1996; Vapnik, 1998; Kecman, 2001).

ANN	Characteristics	Modelling issues	Classification visualisation
MLP	As RBF and SVM, it is also universal function approximator, given sufficient number of neurons and layers. Error backpropagation (steepest gradient) learning.	Relatively slow learning algorithm compared to RBF. Challenge in choosing the optimal structure. Local minima problem.	
RBF	Learning algorithm is faster than MLP. Two-stage learning algorithm: 1. Unsupervised fitting classes with kernel functions (Gaussian RBF) and 2. Supervised, linear optimisation of output weights.	Choosing the number of hidden layer neurons. Data analysis - unsupervised learning may be applied to identify the number of clusters – indicative to number of hidden layer neurons.	
SVM	Learning optimisation aimed to maximise the distance between the class separation function, ensuring improved generalisation from initially smaller data sets.	Data analysis may help choosing a kernel function for optimal linear and nonlinear separation tasks. Decision boundary (- - -) is represented as a hyper plane in n-dimensional space.	

Note: "…different learning strategies do not have to lead to different models. It is not an easy task to categorize various learning approaches because increasingly mixed (blended) techniques are used in training today." (Kecman, 2001, p. 171).

The SVM decision boundary function is optimised based on sparse available training data, without *a priori* knowledge of the underlying probability distribution of the *data universe*. These popular early models (MLP, RBF and SVM) are still in use, across a diverse and growing range of disciplines (Schöllhorn, Jäger, & Janssen, 2008), and are commonly benchmarked against the variations of learning algorithms or newer COS models.

Advantageous properties of ANN applications relevant to the problems being addressed here include: (non-linear, high-dimensional) approximation and classification capabilities, learning from data, resilience to noise and generalisation capabilities, parallel processing architectures, extensive cross-discipline applications and independent methodology development for learning algorithms and changing internal COS structures.

Major disadvantages of traditional COS include: difficulty in pre-selecting the system architecture, catastrophic forgetting, excessive training, and lack of knowledge representation facilities (Kasabov, 2002, pp. 24-25). To advance the discipline, the same author considered these disadvantages and identified the need for improved connectionist and hybrid methods and techniques for learning algorithms and system development under the banner of evolving connectionist systems.

2.3 Evolving Connectionist Systems

The evolving connectionist systems (ECOS) methodology (Kasabov, 2002) includes the evolving paradigm combined with the strengths of different AI techniques such as rule based systems, ANN and fuzzy logic (Benuskova & Kasabov, 2007). Advancements in the fields of CI, ANN and KE – resulting from Dr. Nikola K. Kasabov's early work (Kasabov, Kim, Watts, & Gray, 1997; Kasabov, 1998b; Kasabov, 1998a) – include: adaptation through incoming data (dynamic changes of internal structure, set of parameters or by performance optimisation of objective function of internal structure); and adaptive learning (on-line/off-line, incremental and life-long) that is sufficiently flexible to learn new incoming data patterns without fully destroying previously formed machine knowledge; rule extraction and adaptation.

Combining fuzzy set theory (Zadeh, 1965) and ANN, Dr. Takeshi Yamakawa introduced the 'Neo-fuzzy neuron' and its hardware implementation (Yamakawa, 1990, 1993; Furukawa & Yamakawa, 1995; Miki & Yamakawa, 1995; Yamakawa, 1996; Yamakawa & Uchino, 1997) advancing the state of electronics devices and electronic regulators. From the connectionist systems perspective, this breakthrough meant the availability of an explanation facility i.e. to present internalised machine knowledge to humans in the form of if-then-else fuzzy rules. Figure III-5 represents the concept of rule insertion and extraction from a fuzzy neural network. Since the introduction of the neo-fuzzy neuron, "different types of fuzzy neural networks have been developed and applied to different tasks. A fuzzy neural networks (FNN) is a connectionist model for fuzzy rules implementation and inference." (Kasabov, 1996).

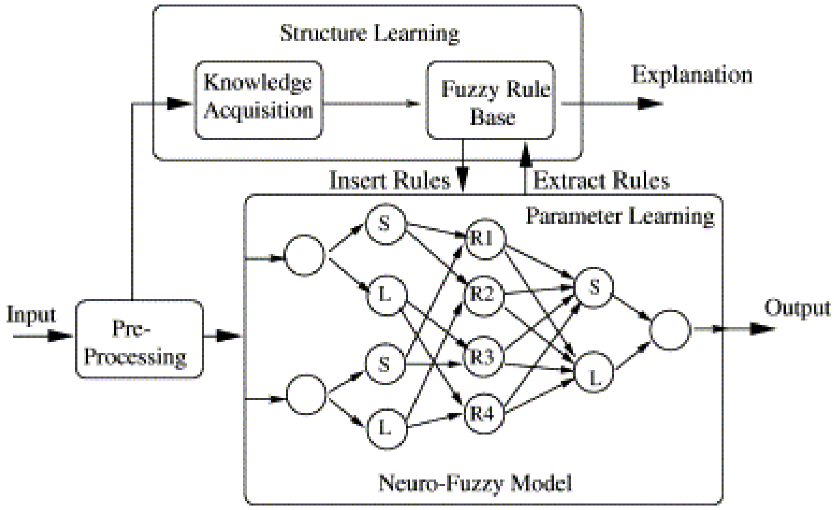


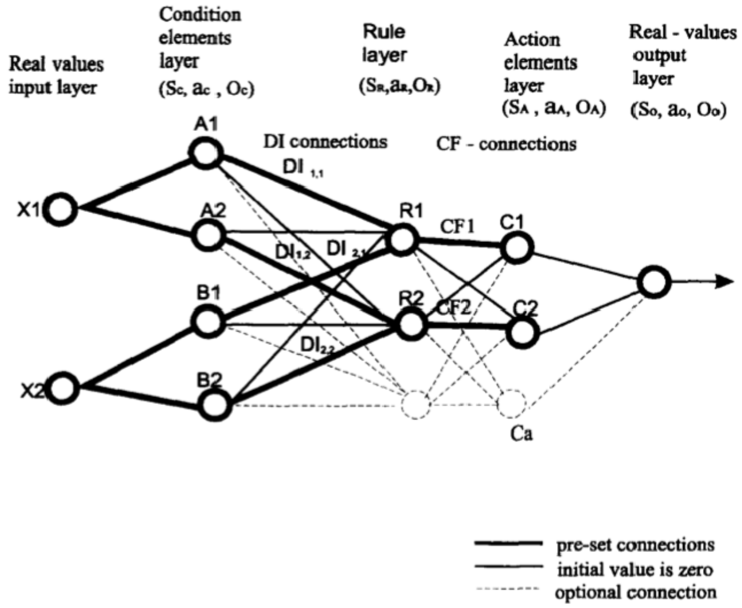
Figure III-5. A general schematic diagram of neuro-fuzzy HyFIS (Kim & Kasabov, 1999; Kasabov, 2002), supporting both numerical data and fuzzy rules as internalised knowledge representation facility.

One of the first adaptive fuzzy neural network (FuNN) architectures (Figure III-6) for adaptive learning and knowledge acquisition was published in (Kasabov, 1996; Kasabov et al., 1997). The past decade of Kasabov's contribution (Watts, 2009) was referenced with the word "evolving" systems rather than "adaptive", with merits of a broader context[6], meaning systems that can change through time.

Relevant to this thesis, ECOS operation exhibits incremental/adaptive and life-long learning – which allows machine knowledge to grow starting from a relatively small initial data set, optimising the internal structure (extracting and storing internal structure into a database where needed), and continuing to learn as more data becomes available. With the facility to initialise ECOS with previously stored extracted knowledge, such ECOS can continue operation in supervised mode, therefore autonomously 'growing' the system knowledge in 'adaptive' fashion as directed by a user and supplied data. In a fictitious scenario a user may take a 'snapshot' of global assessment machine knowledge, apply new data with additional assessment criteria ('bending the rules' for a specific targeted coaching session or individual style) and undo/redo changes of machine assessment as needed. In addition to individual style acceptance, in sport science it is also common knowledge that techniques and performance evolve due to new findings and new sport equipment technologies.

[6] Different meaning than evolutionary computation, associated with genetic algorithms and related techniques.

(a)



(b)

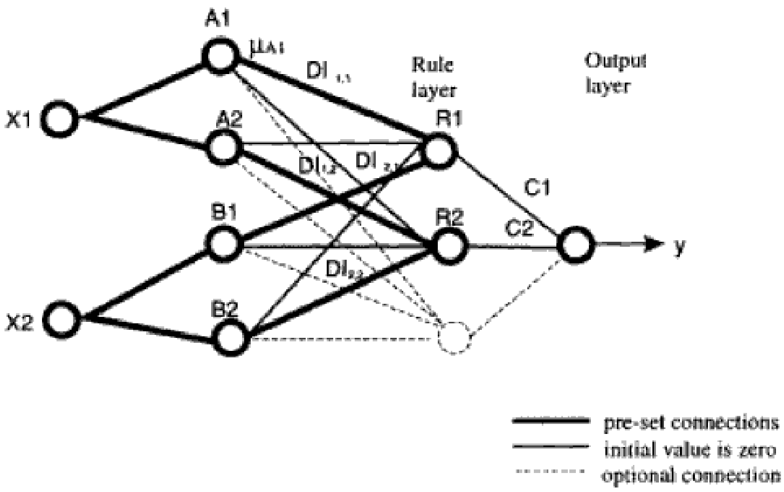


Figure III-6. Foundations of adaptive fuzzy neural networks architecture. (a) Five layers FuNN structure (Kasabov et al., 1997) and (b) a simplified four layers version of a FuNN structure (Kasabov, 1996, p. 321).

2.3.1 Evolving Classification Function - Clustering based ECOS

Evolving Classification Function (ECF) is one of Kasabov's examples of ECOS, used widely to address various classification problems including those characterised with small data sets (Bacic & Zhang, 2004; Ghobakhlou, Zhang, & Kasabov, 2004; Huang, Song, & Kasabov, 2005; Kasabov, 2007b; Kasabov et al., 2008; Kasabov, 2009). ECF is based on the evolving fuzzy neural network (EFuNN) concepts (Kasabov, 1998b) supporting: (1) Adaptive FuNN i.e. neuro-fuzzy architecture; (2) Clustering based evolving machine learning; (3) Incremental learning with dynamic change of internalised structure; and (4) Rule extraction as internalised snapshot of generalised machine knowledge.

As a four layer architecture, in ECF there are no fuzzy output nodes (see Figure III-7 and comparison in Figure III-6) as each evolving rule-node (rule layer – 3) represents a cluster centre of input vectors that belong to the same output class using a defined maximum cluster radius *Rmax* with the use of Euclidean distance (Kasabov, 2007b).

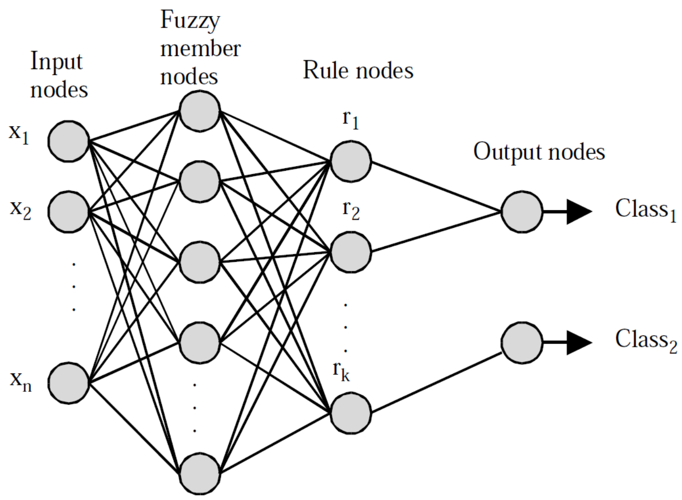


Figure III-7. A simplified structure of an evolving classifier function ECF (Kasabov, 2007a, p. 96).

The underlying *evolving clustering method* (ECM) for ECF is achieved in on-line, one-pass dynamic distance-based clustering, which is suitable for tasks that require fast learning (as shown in Figure III-8 and Table III-5) and recall/classification (Table III-6). The number of clusters with their properties is unknown as it evolves during the learning task and the algorithm does not keep any information of past input data examples (Kasabov & Song, 2002). As there is no predefined number of clusters in a distance-based clustering method the cluster centres are represented by evolved nodes in adaptive mode (Kasabov, 2007a).

For off-line learning tasks, internal clusters that are produced in one-pass can be further optimised by applying ECM with constrained optimisation ECMc (Kasabov, 2002; Kasabov & Song, 2002) for the purpose of improving *generalisation* and *classification*.

On-line Evolving Clustering Method

Incremental learning with dynamic change of internalised structure is described on a two-dimensional example of incoming on-line input data sequence $x_1 \ldots x_9$. The sequence of consecutive input examples and resulting change of internal clustering structure is described as follows:

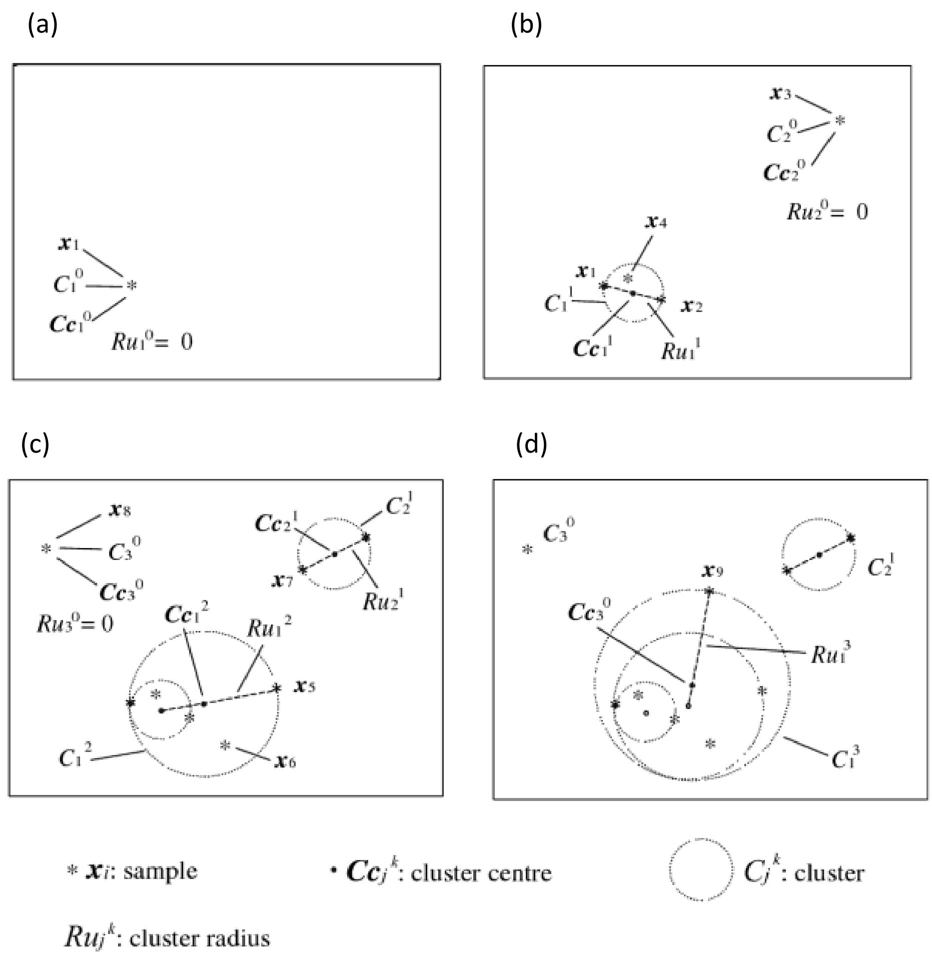


Figure III-8. The example of the evolving clustering process of ECM with input data sequence $x_1 \ldots x_9$ (Kasabov, 2002, p. 41).

(Figure III-8 a)
x_1 … create a new cluster C_1^0 (Figure III-8 b)
x_2 … update cluster $C_1^0 \rightarrow C_1^1$
x_3 … create a new cluster C_2^0
x_4 … do nothing

(Figure III-8 c)
x_5 … update cluster $C_1^1 \rightarrow C_1^2$
x_6 … do nothing
x_7 … update cluster $C_2^0 \rightarrow C_2^1$
x_8…create a new cluster C_3^0 (Figure III-8 d)
x_9 … update cluster $C_1^2 \rightarrow C_1^3$.

As a result of more incoming data, some existing clusters will be updated through changing their centre's positions with increasing radii.

A cluster may be updated depending on the pre-set threshold radius *Dthr*, and the distance D_{ij} between the current data sample x_i. Used as default example of distance calculations $D_{ij} = \|x_i - Cc_j\|, j = 1,2,...,n$, the normalised Euclidean distance formula (III-4) in ECM is further presented in (Kasabov & Song, 2002).

Table III-5. The ECF learning algorithm (Benuskova & Kasabov, 2007; Kasabov, 2007b).

1. Enter the current input vector from the data set (stream) and calculate the distances between this vector and all rule nodes already created using Euclidean distance (by default). If there is no node created, create the first one that has the coordinates of the first input vector attached as input connection weights. 2. If all calculated distances between the new input vector and the existing rule nodes are greater than a max-radius parameter R_{max}, a new rule node is created. The position of the new rule node is the same as the current vector in the input data space and the radius of its receptive field is set to the min-radius parameter R_{min}; the algorithm goes to step 1; otherwise it goes to the next step. 3. If there is a rule node with a distance to the current input vector less than or equal to its radius and its class is the same as the class of the new vector, nothing will be changed; go to step 1; otherwise: 4. If there is a rule node with a distance to the input vector less than or equal to its radius and its class is different from those of the input vector, its influence field is reduced. The radius of the new field is set to the larger value from the two numbers: distance minus the min-radius; min-radius. New node is created as in 2 to represent the new data vector. 5. If there is a rule node with a distance to the input vector less than or equal to the max-radius, and its class is the same as of the input vector's, enlarge the influence field by taking the distance as a new radius if only such enlarged field does not cover any other rule nodes which belong to a different class; otherwise, create a new rule node in the same way as in step 2, and go to step 1.

Table III-6. The classification algorithm (recall in trained ECF) (Benuskova & Kasabov, 2007; Kasabov, 2007b).

1. Enter the new vector in the ECF trained system; If the new input vector lies within the field of one or more rule nodes associated with one class, the vector is classified in this class; 2. If the input vector lies within the fields of two or more rule nodes associated with different classes, the vector will belong to the class corresponding to the closest rule node. 3. If the input vector does not lie within any field, then take *m* highest activated by the new vector rule nodes, and calculate the average distances from the vector to the nodes with the same class; the vector will belong to the class corresponding to the smallest average distance.

The ECF initialisation parameters:

Rmax, *Rmin*, … maximum and minimum clusters radii
Input MF … number of fuzzy membership functions (e.g. 1,2,3, …)
m-of-n … see Table III-6, recall step 3 (e.g. 1,2,3, …)
No. of epochs … number of iterations for training (e.g. 1 for one-pass; and 2,3, … *n* for off-line, multi-pass learning).

Normalised Euclidean distance E between points a and b in n-dimensional space:

$$E = \sqrt{\frac{1}{n}\sum_{i=0}^{n}(a_i - b_i)^2} = \|a - b\| \qquad \text{(III-4)}$$

Off-line Evolving Clustering Method Optimisation

For off-line classification tasks, an off-line version of ECM optimisation supports the internal consolidation of machine knowledge. Given the general benefits of ECOS and the specific nature of incremental learning, the ECM enables mixed application/operation scenarios such as: on-line, off-line, rule extraction (externally stored machine knowledge associated with data and task) and then on-line operation on new data, which permits further internal machine knowledge adaptation. For augmented coaching systems, this allows a coach to e.g: (1) Store a 'snapshot' of trained machine automated assessment; (2) Apply new skill variation and assessment criteria; (3) Augment machine knowledge if there is improvements in the learner's technique evident in the machine assessment; or (4) 'Undo' changes by abandoning new technique changes if proven not successful.

A coach may also keep machine knowledge as their intellectual property if the system assessment accuracy achieved – based on their supervised learning – is higher than others. From a machine learning perspective, improved generalisation (as a result of internal consolidation of machine knowledge) may lead to improved classification performance including classification tasks on small available data sets (investigated in Chapters 6 and 7). As an example of the extension of ECM global off-line optimisation, an evolving clustering method with constrained minimization (ECMc) was introduced in (Kasabov & Song, 2002).

Table III-7. The ECMc evolving clustering algorithm with constraint optimisation (Kasabov, 2007a, p. 65).

Step 1: Initialise the cluster centres Cc_j, j = 1, 2, …, n, that are produced through the adaptive evolving clustering method ECM. Step 2: Determine the membership matrix *U* Step 3: Employ the constrained minimisation method to modify the cluster centres. Step 4: Calculate the objective function *J* Step 5: Stop, if: (1) the result is below a certain tolerance value, or (2) the improvement of the result when compared with the previous iteration is below a certain threshold, or (3) the iteration number of minimizing operation is over a certain value. Else, the algorithm returns to Step 2.

Where:
The objective function *J*:

$$J = \sum_{j=1}^{n} J_j = \sum_{j=1}^{n}\left(\sum_{x_i \in C_j}^{n} \left\| x_i - Cc_j \right\|\right);\ i = 1,2,\ldots p \qquad \text{(III-5)}$$

As tolerance value, the maximum distance from any cluster centre Cc_j to the examples that belong to this cluster is not greater than the threshold value, *Dthr*. Constraint *Dthr* as a cluster threshold value is defined as:

$$\left\| x_i - Cc_j \right\| \le Dthr\ ;\ i = 1,2,\ldots p\ ;\ j = 1,2,\ldots n \qquad \text{(III-6)}$$

The partitioned clusters are defined by a $p \times n$ binary membership matrix *U*, where each element $u_{i,j}$ is 1 if the i^{th} data point x_i belongs to cluster j; and 0 otherwise (Table III-8).

Table III-8. Assigning values 0 or 1 to binary membership matrix *U.*

FOR $j = 1,2,\ldots n$; $k = 1,2,\ldots n$ DO
IF $\left\| x_i - Cc_j \right\| \le \left\| x_i - Cc_k \right\|$ AND $\forall (j \ne k)$ THEN $u_{i,j} = 1$;
ELSE $u_{i,j} = 0$; END IF
END DO

Once the cluster centres Cc_j are defined, the minimising values u_{ij} are derived for (III-5) and (III-6). The iterative ECMc technique applies cluster centre optimisation based on normalised Euclidean distance (III-4) as a measure between an example vector x_k, belonging to a cluster C_j , and the corresponding cluster centre Cc_j , as described with the algorithm (Table III-7).

An ECMc addresses the problem of cluster centres not being at the centre of gravity due to the unpredictable random nature of on-line input (Figure III-8) (Hwang, 2009). The ECMc optimises the existing cluster centres (derived from the online ECM algorithm) and moves the cluster centres to the centre of gravity. Once the cluster centres are updated, the input vectors are reallocated to the nearest cluster.

3. Open Problems from the Connectionist Perspective: A View

According to Kasabov (1996, p. 15), good candidates for finding solutions to the main problems in *expert systems* design are fuzzy systems and neural networks. The main problems in building expert systems and a thesis perspective are summarised in Table III-9.

Table III-9. Recommendations and thesis perspective.

Problem		Recommendations and thesis perspective
1.	How to acquire knowledge from experts?	By visualisation and replay of motion data. Capturing implicit expert's knowledge by supervised learning.
2.	How to elicit knowledge from previously collected large data?	By investigating the rule extraction techniques and approaches that enable modelling of heuristics and coaching rules as means of eliciting knowledge and feedback from connectionist systems.
3.	How to represent incomplete, ambiguous, corrupted or contradictory data and knowledge?	By capturing motion data for the case studies that may include: Imprecision, small or unbalanced data set, presence of hard-to-quantify systematic error, data that are ambiguous (e.g. not strictly adhering to isolated skill level), overlapping or transformations to feature data that are not intelligible to human reasoning.

Problem		Recommendations and thesis perspective
4.	How to perform approximate reasoning?	Via developing the artefacts for human motion data modelling and data analysis relying on connectionist approaches. The application of ANN is motivated by their ability to always produce output on data that may be e.g. incomplete, ambiguous or imprecise.

In comparing fuzzy systems and neural networks (Kecman, 2001, p. 11), fuzzy systems require no data and can operate on structured expert's knowledge typically codified as IF-THEN rules, while artificial neural networks require no previous knowledge but they learn from data – as measurements, observations or records of known data pairs. Inline with the research questions of the thesis (p. 32), this indicates that it may be possible to build expert system components that can capture an expert's implicit knowledge via learning from data and to perform approximate reasoning from measurements or observations.

Table III-10 addresses some of the known open problems in regard to *evolving connectionist systems* (Kasabov, 2007a) to illustrate the perspective of this thesis, along with the classifier modelling strategies adopted in this research.

Table III-10. Thesis perspective relative to a subset of open problems introduced in (Kasabov, 2007a, p. 29).

Open problem		Recommendations and thesis perspective
1.	"How do we identify the type of problem space and the dimensionality in which processes is evolving"?	With minimal or no prior work in this research domain, the expert guidance and data are starting points in model design and feature extraction and space reduction techniques. Initial data set for a prototype system may be captured at higher resolution than for the target system. Reasonably good results with reduced dimensionality may indicate discriminative properties of features in problem space and indicate direction in practical implementation design strategy.
2.	"Most of the models use time as a linear variable, but is that the only way to present it"?	This thesis focus is on temporal event recognition and temporal and spatial (dynamic and static) feature extraction techniques (Chapters 6 and 7).
3.	"How do we define the best model for the purpose of modelling an evolving process"?	From data, application and CS context. For initial data set and prototyping (Chapter 6) there are different priorities for modelling context (Figure IV-4) than for larger and possibly representative data sets (Chapter 7).

Open problem	Recommendations and thesis perspective
4. "Can a system become faster and more efficient than humans in acquiring intelligence, e.g. in learning multiple languages"?	Directing focus on high-level properties transferable among diverse sports and related disciplines. For example: Software engineering should promote design of reusable modules, incremental design and flexible architectures with upgradeable structural elements. As concurred with (Knudson & Morrison, 2002), kinesiology and biomechanics should promote inter discipline publications including error and feedback taxonomies – transferable to CI data analysis and system design.

4. Chapter Conclusion

Supported by the review of existing work including the gap in augmented coaching systems, the following decisions have influenced the scope of the thesis:

- Applying methods of AI/CI to automate elements of qualitative analysis of human motion – known to be difficult to implement using traditional computational approaches;
- Selecting established models of qualitative analysis of human motion is based on their potential to be transferred to general applications of CI and connectionist approaches in data analysis and modelling of human motion. Similar to existing models and systematic observational strategies (flexible and applicable to diverse sport domains), a new systematic framework(s) including data and heuristic acquisition to machine feature transformation as well as general connectionist methods for motion data should be investigated and proposed;
- Existing selection of established models of qualitative analysis, applicable to diverse sport disciplines to be utilised to: establish the research scope; provide rationale for boundaries; and validation of derived heuristics;
- Model validation – established in machine learning as a measure of predictive/classification power – compared to a human expert or other reliable comparative measure. For human (expert and external) validations including motion data analysis and qualitative technique assessment, specialised visualisation tools (Alderson & Elliott, 2006) are required. The appropriate validation method for connectionist approaches is to be chosen based on data analysis, taking into

considerations data set properties such as size relative to problem dimensionality and data distribution;

- Need for flexible machine analysis of motion data. Investigation of aspects equivalent to qualitative analysis include: machine implementation of common-sense heuristics, descriptive assessment categories, coach's cues, expert's subjective criteria and explanation of machine assessment/analysis back to human. Utilising *supervised learning* technique and classifier modelling could lead to achieving motion pattern matching to a number of discrete categories based on subjective criteria captured from a domain expert/coach;
- Need for critical analysis to provide insights from numeric data such as data set properties and knowledge discovery common to knowledge engineering discipline; and
- Supporting discipline inclusion such as established software engineering principles on designing reusable and interchangeable software components. Abstract system function and concepts to be designed for human use including human computer interaction principles.

Application prototyping should include critical elements required for validation of connectionist approaches and illustration of possible scenarios for the development of augmented coaching systems.

Insights from this thesis should lead to opportunities for continuing future research such as instruction and intervention feedback to learners and the further bridging of CI with related disciplines.

C h a p t e r   4

IV. A NOVEL SYSTEMATIC FRAMEWORK FOR MOTION DATA ANALYSIS AND MODELLING

Chapters 2-3 presented multi-discipline methods leading to a new domain in automating aspects of qualitative analysis in sport and related disciplines.

In this chapter combining computer science with descriptive paradigms of natural science is viewed as providing important links between CI, software engineering and modelling of phenomena in their natural contexts. This chapter covers:

1. Critical analysis on human motion learning and connectionist modelling for the purpose of bridging disciplines.
2. Methodology and a connectionist framework for creation of ACS and human motion modelling and analysis in sporting activities. The key elements are:
   - Augmented coaching system framework;
   - Modelling and an incremental design framework for the instantiated multi-modular data processing operating on evolving principles; and
   - A generic research framework for cross-discipline motion data analysis and modelling purposes. This includes: (1) spatial and temporal feature extraction techniques and (2) strategic consideration of feature extraction algorithm design.
3. Mental models related to the following contexts: (1) classifier modelling properties, (2) motion data acquisition for ACS and (3) coaching scenario linked to personalisation aspects (e.g. goals, skill level, subjective and flexible assessments).

1. Problem Analysis: Applying Computational Intelligence to Kinesiology

> ***The process of matching current data from the domain space to the existing knowledge and inferring new facts until a solution in the solution space is reached.***

Nikola Kasabov, Inference of an AI system

This section provides problem analysis of modelling human motion in sporting activities and the relationships among the concepts pertinent to augmented coaching.

1.1 Capturing Human Inference for Machine Learning

Similar to some degree to the processes used in human learning (Chapter 2, Table II-3) of motor skills, an automated system can be designed to assess motion in terms of its adherence to a set of rules and ranges of correctness (Table IV-1). As pointed out in Dreyfus et al. (1986), expert reasoning is not necessarily bounded by a set of explicit rules; rather the rules that govern decision-making processes may be internalised in the human mind. Gestalt cognitive principles, grouping based on proximity and similarity or other pattern recognition properties of an expert's mind can be captured to some degree as learning from examples – commonly referred to in CI as (machine) *supervised learning*.

In a supervised learning scenario, the resulting expert classification is captured along with each data sample and presented to a classifier, which after initial *training* may autonomously categorise/*classify* unseen or future data.

For relatively small and mid-size data sets, capturing an expert's reasoning on examples (as *expert labelling*) may be a more efficient approach in system design than trying to capture and implement all 'common sense' rules guiding the expert's reasoning. For relatively large data sets, the output labels can also be obtained as measured outcomes from the system's operating environment e.g. impact angles, ball flight descriptive category. Utilising measured KR instead of the experts' KP assessment may represent a practical modelling alternative to predictions, heuristics/CR testing, and modelling and data analysis.

The rendered rules governing machine classification may be extracted and presented in an intelligible way to a human mind. Examples of situations in which machine-generated knowledge may be challenging for a human to understand are when the number of rendered rules may be very large; or when they are determined as a result of mathematical functions (FET, space reduction method) or transformations (e.g. *principal component analysis*, *linear discriminant analysis*, Chapters 3 and 7) that for the human mind are non-reversible.

1.1.1 Assessment by Similarity Comparisons

Just as humans generally focus their analysis on critical features of a specific motion event, motion data analysis may include defining a range of correctness for a specific feature, mental adherence to a perceived 'ideal image', comparisons to heuristic rules and various contexts influencing the 'big picture' – a top down human assessment concept.

Table IV-1. Performance assessment and CI.

Assessment	Design/Implementation considerations
1. Observation and 'ideal image' comparisons.	'Top-down' cognitive assessment. Gestalt principles. Implementation challenge, requiring CI/KE methods such as connectionist systems, orchestrated structures of multiple connectionist systems.
2. Adherence to descriptive heuristics comparison.	Simplified set of 'common-sense' rules (heuristics) referring to expert's mental model and comparisons or categorisations of performance. With combined systematic observation strategies, problem area may exhibit both 'top-down' and 'bottom-up' assessment properties (see the next chapter).
3. Comparisons by 'range of values'.	Predominant 'bottom-up' assessment. Implementation strategy may involve both traditional and CI approaches.

The abstract cognitive process embedded in a coach's mind when diagnosing a motion event may be described as comparative adherence to an 'ideal image'. Arguably, such a capability of the human mind enables the assessment of previously unseen personalised motion techniques, as well as grouping based on previously seen similar motion techniques. Even with previously unseen motion technique events a coach can 'intuitively' assess efficacy, effectiveness and other assessment rationales. From a 'big picture' perspective a coach may learn about a new personalised technique and provide diagnosis in a relatively short time. From a design perspective (Table IV-1), evolving models are able to accommodate incremental learning of evolved techniques; although the machine implementation of abstract cognitive processes is still a challenge for modern CI discipline. In contrast, in biomechanics, the assessment of quantifiable performance properties, such as the correct or incorrect range of measured values, may be considered relatively easy to automate.

The capacity to personalise both assessment and feedback should accommodate individual variations in terms of ranges of correctness. Also accounting for the possibility of multiple coaches' diverse opinions (e.g. influenced by prior knowledge or the learner's background), personalisation may require data management functionality for diverse assessment criteria for the same observed set of motion events.

1.1.2 Modelling Observations and Grouping by Similarity

In observing movements through the impact zone in diverse sports (Figure IV-1), some sport categories tend to have more linear movement throughout the action zone (found in javelin throw, pool/snooker) compared to other movements that are non-linear (including the circular movements found in cricket bowling, batting or in racquet sports), while some incorporate both movements (such as the martial arts).

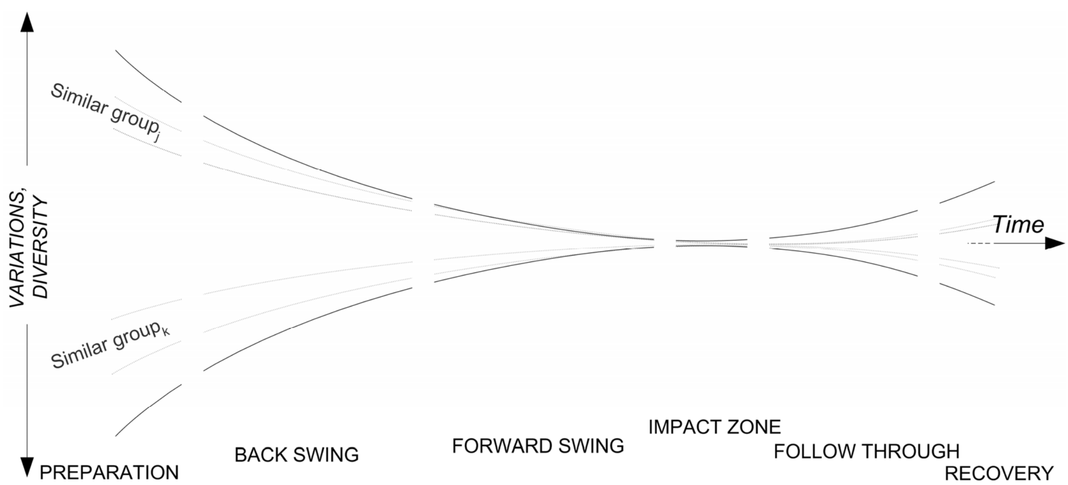


Figure IV-1. Diversity of personalised technique through temporal phasing in diverse sport disciplines. Abstract image showing variations between stroke, swing, kick or throw groups. Observed individual diversity in characteristic groups' stroke, swing, kick or throw is evident through different temporal segments, but there is greatest similarity through the action/impact zone.

Action/Impact Zone Insights

In observing individual variations of personalised technique, the impact zone seems to be less prone to such variations (e.g. immediately after the impact only the laws of physics apply to a projectile/ball while continuing human motion has no further influence). With this observation, as an initial hypothesis, the impact zone was considered as the best candidate for evolving and traditional (non-evolving) *global assessment* modelling. Global assessment implies a classifier (trained on a data set) that will work well – that is, it will classify accurately – on the associated global *universe* data set (or equivalent *universe*-representative large data set).

In observing movements through the phase segments outside of the impact zone these tend to be more individualised and generally evolving within a sport discipline over time, indicating in part the problem complexity in attempting to find 'the best assessment model'. This observation indicates the necessity to utilise ECOS and other adaptive approaches introduced in previous chapters.

Temporal segmentation for machine learning and similarity grouping is not restricted to sports incorporating an impact/throw/kick zone. It is also generally applicable to other sports such as skating, skateboarding and skiing where the 'impact zone equivalent' or 'action' phase (see temporal and spatial observation model, Chapter 2) would map to the observation of a sub-area of a turn, typically transitioned around maximum ground-resistant force. The target line equivalent is intended direction or in some cases the down-hill line. With connected turns, the end of each recovery phase is associated with an equilibrium state leading to un-weighting, which is typical for the preparation stage of the next turn. Generalising on multiple sport discipline rationale and experiments from the case studies (Chapters 6 and 7), it a philosophical view expressed in this thesis that the impact zone and *(motion) action focus* – as a new term – can be used interchangeably where appropriate.

1.1.3 Personalisation and User Profiles

In the process of acquiring skill proficiency over time (Table II-3), individual learners also develop idiosyncrasies – strengths and weaknesses – that are typically addressed for improvement through individualised coaching attention. From a temporal perspective this leads to open coaching questions, in that in addressing one weakness (or strength) it is possible to diminish other related weaknesses, or on the contrary, it is also possible to introduce a new set of weaknesses requiring more immediate attention[7].

In terms of delivering personalisation, a modular and incremental architecture and framework is required so that a system may adapt to different users and users' profiles. Moreover, a 'user' can be a learner (performer) *or* a coach, the latter having responsibilities regarding assessment criteria settings. Thinking of this issue in terms of connectionist systems, ECOS is preferred for incremental, life-long learning for personalised classifier models. With the opportunity to insert and extract machine knowledge, the interaction model should include database functionality to hold various data such as user profiles, progress history, skill level, CS exercises and global assessment criteria.

From the perspective of knowledge discovery investigation, classification models that can provide machine knowledge (e.g. a set of rules) could be included in validation comparisons with traditional, commonly benchmarked connectionist systems such as RBF, SVM, and the like.

1.2 Categorising Performance: Human and Machine Learning

In the absence of more direct measures, a qualitative assessment may be quantified as 'performance categorisation' by relying on an expert's mind. From the perspective of connectionist systems, a classifier for 'performance categorisation' tasks should be modelled to operate depending on the specific context of human motion activities and rationale of the problem being addressed.

1.2.1 Rationale for Proposed Modular Assessment

A human-intelligible assessable element – instantiated here as a coaching rule (CR) – may be implemented from one or many heuristics (Figure IV-2).

[7] The existence of learner's errors and their relationship may be described as a "chain of errors".

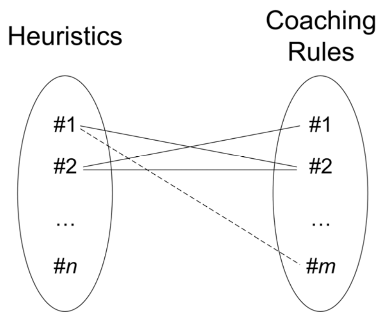


Figure IV-2. 'Many to Many' relationship between sets of heuristics and coaching rules.

For example, a heuristic called 'swing plane' (as a loosely described heuristic concept) could be transferred into similar and yet distinct coaching scenarios (and e.g. task sheets Figure II-7) for baseball, golf or hockey. Both heuristics and coaching rules (more specific description associated to a sport domain) are associated with motion data processing – with assessment automation based on CI approaches.

Common to the experiments conducted in this research is a design rationale supporting the incremental and modular design of ML assessment units – or modules – that collectively contribute to the assessment of a *motion event*[8]*/motion sequence*. Such modules are referred to either as a *Motion Heuristic Evaluation Module* (MoHEM) or as a *Coaching Rule Evaluation Module* (CREM) – as depicted in Figure IV-3.

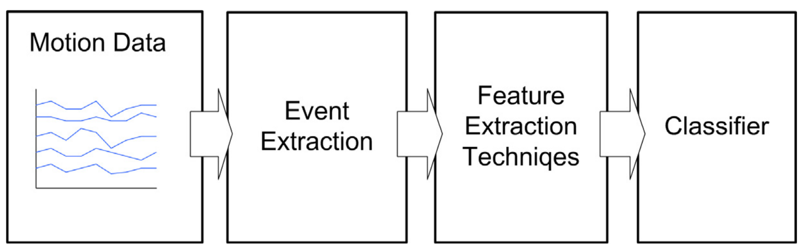


Figure IV-3. MoHEM/CREM design and modelling stages.

Acquired motion data are imported and processed to extract a motion event, in the form of a temporal *Region of Interest* (ROI). The 'Feature Extraction Techniques' modelling stage

[8] Characteristic sequence pattern of e.g. body movements

involves the processing of filtered ROI data that are further mathematically transformed as discriminative numeric properties describing a set of observed critical features (linked to static and dynamic observation focus) forming the input to the classification stage.

1.2.2 Modelling a Classifier

Classifier selection for MoHEM/CREM implementation depends on the application context for a particular motion data set.

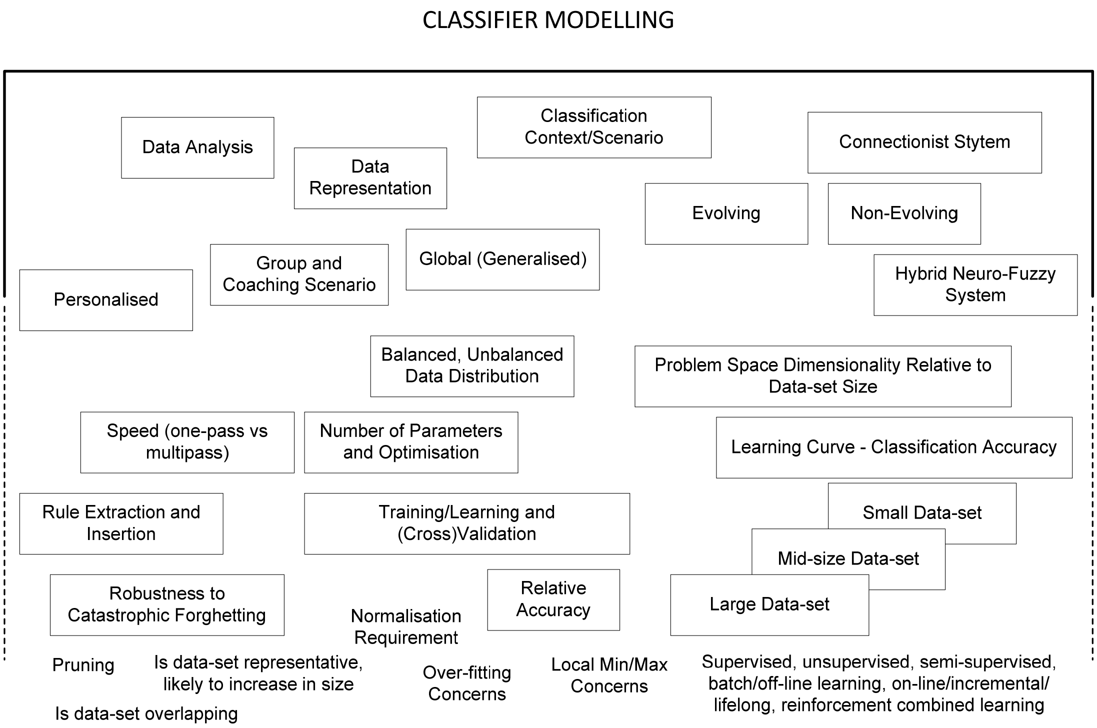


Figure IV-4. Mental model[9] – classifier modelling context and investigation directions. For simplicity, possible relations among diverse properties are omitted.

Although some classifiers are more popular than others for a given classification problem area, at present there is no 'best' or 'single solution' universal classifier. The complexity of the classifier selection problem is exemplified by the mental model in Figure IV-4, and the need for optimisation of various classifier properties for the task. The following two examples illustrate the differences in possible strategies for particular modelling contexts:

---

[9] Linking relations are omitted for simplicity.

1. A labelled data set estimated as mid-size to large, with extensive coverage of the possible *data universe* for a characteristic motion event. Labels are obtained automatically as measured categories of KR outcomes. For the purpose of e.g. *split-sample* or *holdout* validation, the data set is to be reshuffled and divided into training (e.g. 80-90%) and testing (e.g. 20-10%) portions. Both data set portions are to be normalised within diverse ranges to suit a number of connectionist methods. If needed for a particular connectionist method, parameter optimisation techniques may be employed. Both evolving and non-evolving connectionist methods should be considered for a global assessment classifier module.
2. Small labelled data set, possibly with coverage of general novice motion technique. Labels are obtained as discrete categories from an expert's assessment of KP. Pre-processing data analysis may include an interview with the expert to find out e.g. how close the output classes are or any other similarity grouping that may influence the expert's internal decision boundaries. Similar to Gestalt principles (of similarity and proximity), human experts are able to visualise or conceptualise clusters of similar motion event groups, without detailed analysis. Such ability potentially may be leveraged to overcome the limitations imposed by small data sets (Bacic, 2008b); hence the benefit of expert input via interview. Initial prototyping is likely to provide an indication of classification accuracy for a larger data set. Given that we cannot know for certain that a small data set is representative of the associated *data universe*, classifier selection may also include models with few optimisation parameters in addition to commonly used classifiers in model benchmarks such as RBF, SVM and similar. To avoid possible *validation incidents* where, for example, an entire cluster is randomly allocated to the testing portion of a data set, the *leave-one-out* (LOO) or other *cross-validation* techniques are preferred over split-sample validation (as described in the large data set example above).

1.2.3 Need for Personalisation, Coaching Scenarios, Subjective and Flexible Assessment

The range of examples from different profiles' perspective and contexts (Chapter 2 and Table II-4) implies a requirement for personalised and flexible assessment criteria to support validation of a wide range of possible specific targeted activity. A proposed link (Chapter 2, Table II-3) between AI and an established categorisation of human skill implies a requirement for preset programmes to match a certain skill level. Preset assessment and feedback programmes (as specific targeted activities) can be applied: (1) to a group of learners or (2) as general (global) assessment of some of the heuristics that might be typical for a particular skill level or applicable across multiple skill levels.

Coaching Scenario

The concept of a *coaching scenario* (CS), shown in Figure IV-5, enables the user to address variable assessment criteria within specific circumstances.

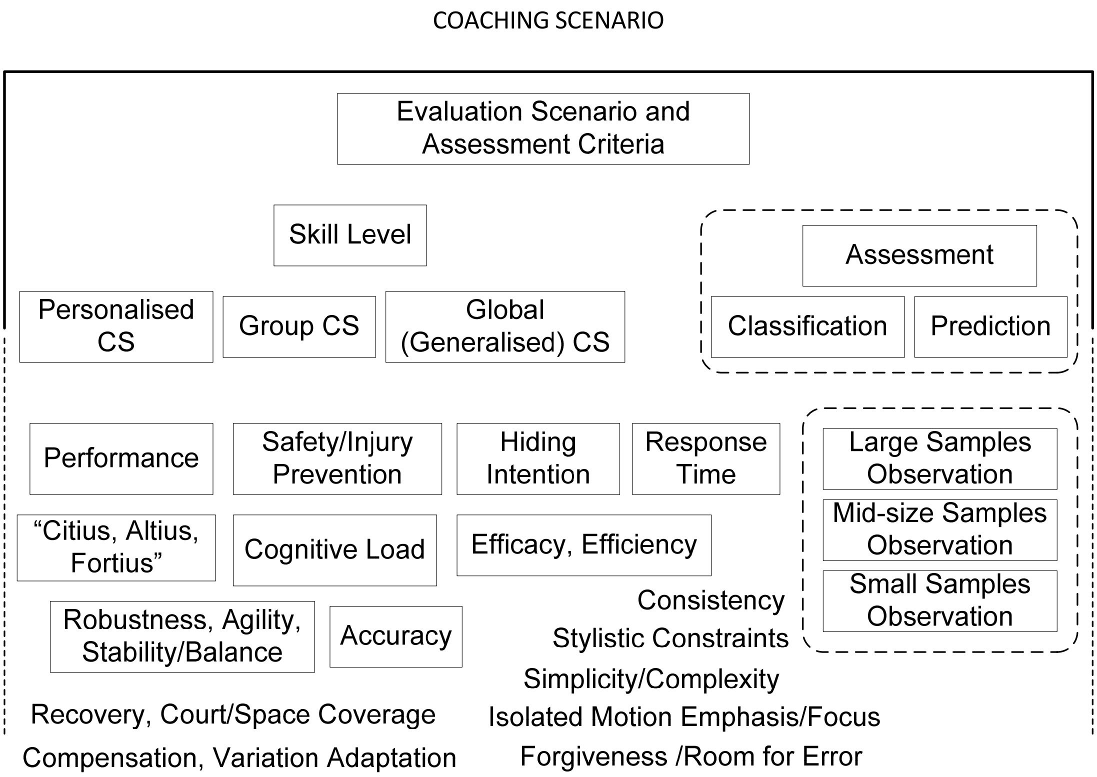


Figure IV-5. Mental model – coaching scenario applications and augmented coaching contexts. Diverse sports may focus on particular goals to be optimised and prioritised in diverse contexts.

Grouped items (Figure IV-5) have a degree of inner connections specific to a connectionist systems methodology. Non-grouped items are associated with diverse and flexible criteria linked to the goal(s) of a movement.

For example:

1. In the coaching process (Chapter 2, Figure II-2) a coach having a set of goals may plan to set or impose a controlled environment (e.g. a practice drill) for a given player, which would help them to focus on a particular aspect of the player's skills, improvements and adaptations.
2. In competitive circumstances, a coach may produce a SWOT analysis to establish a (flexible) set of goals. A learning system can also be trained to perform classification based on subjective criteria (e.g. player's skill level).
3. In sports or injury recovery circumstances, a coach may collaborate with a physiotherapist to gradually introduce in training a set of achievable goals, including helping a player to avoid learning 'bad habits'. In another scenario a player in recovery may be periodically assessed against milestone criteria – as part of a 'back to competition' management strategy.
4. In addressing 'hard to unlearn' coaching challenges, where a coach may design a set of practice drills, which would help to correct 'bad habits' or 'unlearning' phenomena.

In general, CS is linked to the concepts of: *sub-space optimisation, orchestration* and multiple assessment function of MoHEM/CREMs.

CS for Controlled Open to Closed-Skill Training Contexts

For both open and closed-skill sport disciplines, CS may also be linked to focus a learner's attention on a single heuristic or on a subset of available coaching rules. For open-skill sport disciplines, CS goals may also be linked to isolating/controlling the open nature aspects to reduce variation complexity from open to closed-skill sport discipline (Figure IV-6).

Personalisation and Validation – Implementation Perspective

In order to address the necessary validation of expert labelling and possible coaches' disagreements, it should be possible for an individual coach to train the system and generated machine knowledge would be managed externally. This can be achieved by ECOS capabilities of rule extraction/insertion (see Chapter 2) and by a system function enabling coach personalisation data management. Similar off-line operation system functionality can be extended to store learners' prior motion data and therefore to compute individuals' progressive achievements.

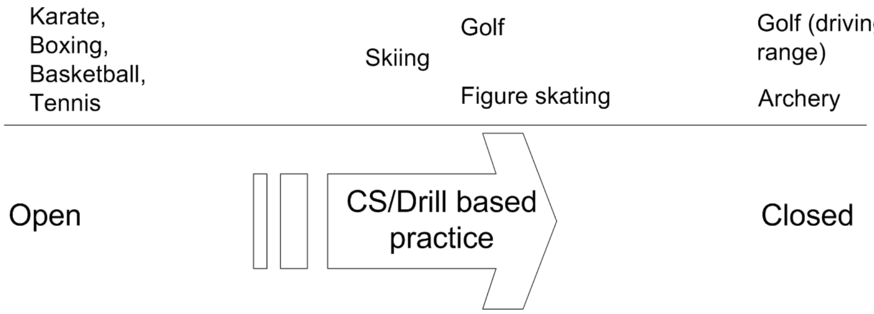


Figure IV-6. Role of coaching scenarios and drill training to focus on diverse goals or to simplify external (open) factors including technique aspects, gauging or reducing interaction with the opponents, environment or team members.

Note: The coaching concept Figure IV-6 is not viewed as the opposite to a concept of 'a challenge during the practice to be harder than in competition' but its purpose is to complement and add variation and use of augmented coaching technology.

2. Augmented Coaching System Framework

The key components of ACS (presented as a block diagram in Figure IV-7) based on CI and evolving connectionist approaches are:

- **The learning system**, a central component responsible for automated diagnostic functionality equivalent to qualitative and quantitative analysis of human motion. Taking input information in the form of motion data, it performs event recognition, feature extraction and assessment diagnostic function based on supplied features. The output of the learning system is conceptualised as *diagnostic outputs*;
- **Supervised learning** of the learning system is based on previous i.e. historical motion data assessment by a coach (domain expert). Lifelong, incremental learning is enabled by applying evolving connectionist approaches;
- **Intervention** and environment control is considered as a component that is extending the feedback optimisation function[10];
- **A coach** should be responsible for:

[10] Disambiguation note: From software engineering perspective, intervention is viewed in this thesis as a module connected to the feedback module. In kinesiology feedback is considered as part of intervention (Chapter 2).

- Identifying the goal(s) of movement appropriate for the learner's personalised profile, which is to be assessed based on subjective criteria. Subjective criteria are therefore based on: the goal of the movement as well as the subject's skill level and other personal idiosyncrasies.
- Interacting with the learning system, rules, and feedback linked to subsequent intervention and control components;

- **Learner**, who is learning by performing a motion-oriented task (sport activity), which is captured, assessed and returned as a set of multi-modal instructions intended to improve a particular aspect of that captured motion for recurring activities. Multi-modal instruction should be based on educational principles combined with appropriate supporting ICT infrastructure; and
- **Rules**, extracted machine rules (Chapter 3) of the learning system's inference as a snapshot in time that may be reflect global, group or personal assessment based on subjective criteria.

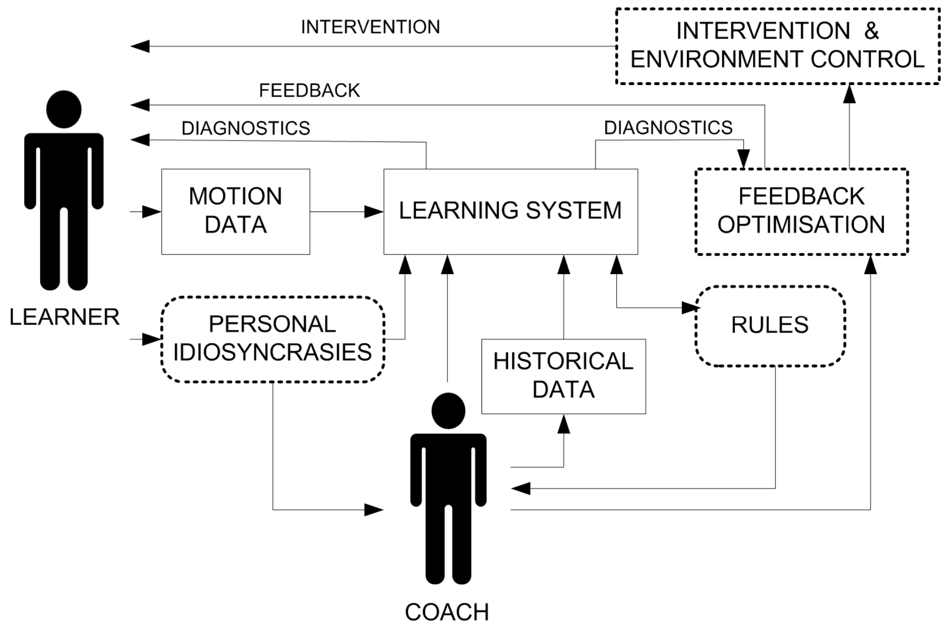


Figure IV-7. Augmented coaching systems. Evolving synergy between human learning and machine learning systems.

3. Augmented Coaching Model Design

In general, an ACS should process motion data captured during the observation task, evaluate human performance, compute a diagnosis, and provide feedback linked to a desired intervention.

3.1 Learning System Architecture

The learning system proposed here (Figure IV-7 and Figure IV-8) supports the following concepts and capabilities:

- Modular assessment of quantitative and qualitative motion data analysis. This includes: heuristics, coaching rules and characteristic motion event pattern recognition. The CI approach advocated in this thesis enables data processing of combined body parts (e.g. pelvis, arm and shoulder action);
- An end-user can see diagnostic outputs as individual assessment results of individual *diagnostic elements* as CREM/MoHEM mapped to CR or Heuristics;
- Personal idiosyncrasies, skill levels and flexible assessment criteria are accommodated by ECOS training or insertion of prior extracted rules stored as machine knowledge (also called an *expert knowledge* base). Incremental learning of trained modules is facilitated by ECOS; and
- For the evolving nature of sports, modular components (e.g. MoHEM/CREMs) can be incrementally developed then added, deleted or replaced in a system.

The 'Motion Event Extraction' module (Figure IV-8) provides characteristic event-type recognition functionality. The 'Rule Module Selector' is responsible for enabling/disabling MoHEM/CREMs by utilising user-configurable selection or input data associated with recognition of motion event type.

LEARNING SYSTEM ARCHITECTURE

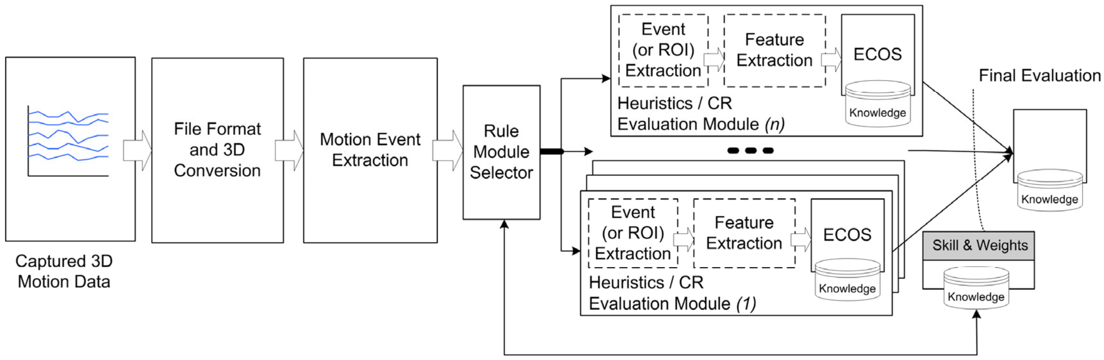


Figure IV-8 General learning system architecture for on-line and off-line data processing in augmented coaching.

3.2 Generic Modelling Framework for Augmented Coaching

Collecting context, insights and knowledge of a motion activity are considered as the key elements of preparation for prototyping or incremental model/system design.

For prototyping (Figure IV-9), the following assertions are considered:

- Automation goals are identified to form ML transferable hypotheses linked to heuristics and CR;
- Expert-based event or activity recognition is to be recorded with motion data;
- Event recognition automation may not be included in the initial model;
- A motion event is considered as a data sample;
- The initial data set should contain a variety of motion events for targeted skill level(s) comprising heuristics and coaching rules. A variety of captured motion events should be included in data analysis in terms of output class (output label) distribution; and
- Initial modelling is focused on identifying (machine-transferable) features, followed by feasibility investigation and design optimisation strategies that may be subject to cyclic improvements.

Techniques for implementing machine feature selection and transformation include both qualitative and quantitative approaches.

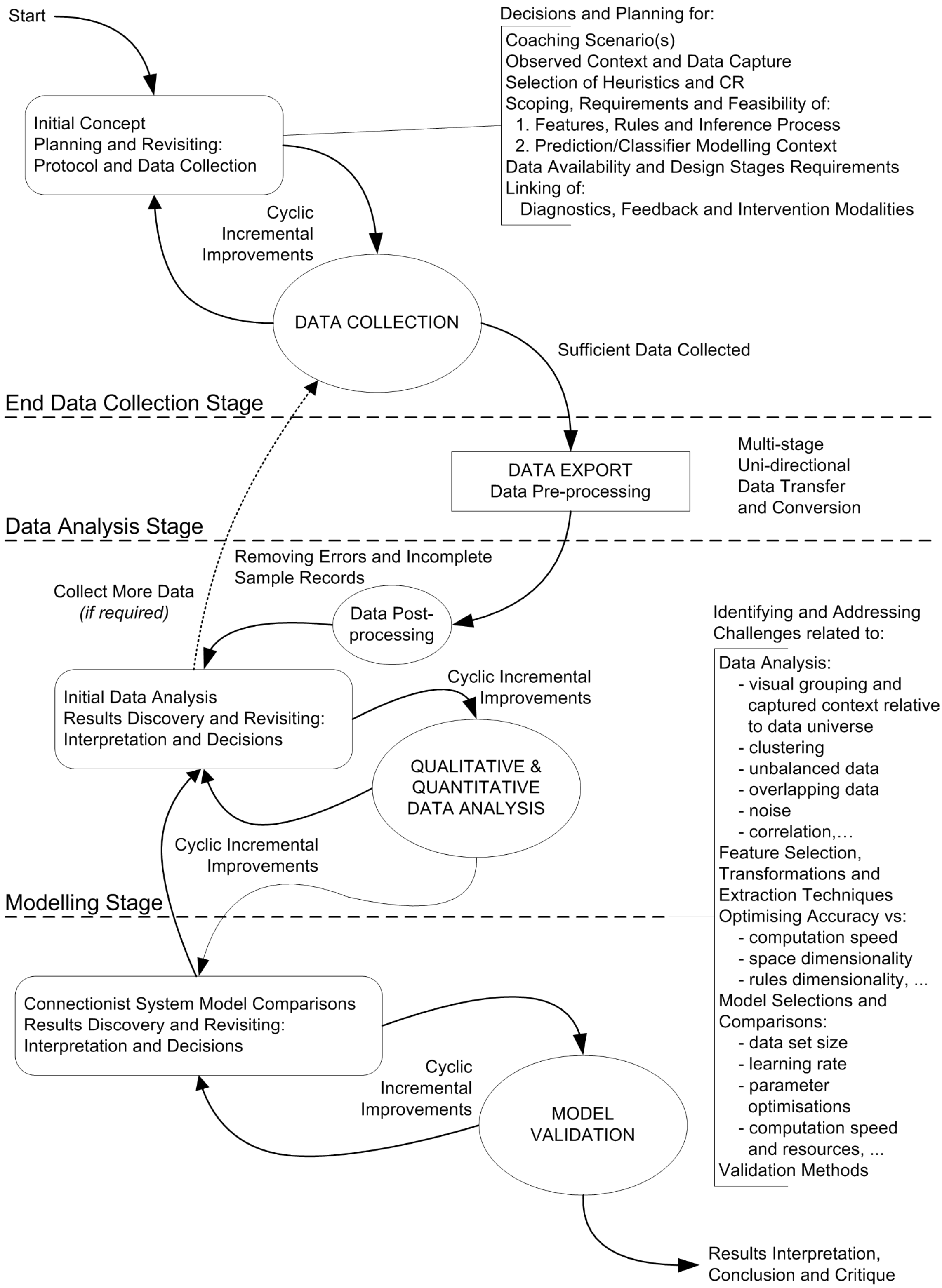


Figure IV-9. Generic modelling, prototyping and investigation stages. Stages on the left hand side are matched with KE/CI approaches and potential challenges.

3.3 Modelling Framework for Modular Design of Augmented Coaching Systems

The intent of the instantiated framework supporting the modular design of an augmented coaching system is to: (1) Automate components responsible for performance assessments; (2) Minimise data format dependence by separating processing into specific stages, in which each stage has a high degree of reusable purpose; and (3) Make modular components to some degree transferable among sports and related disciplines.
In this thesis, to support/augment human qualitative analyses, the notion of the *Coaching Scenario* (CS) is used to unify the architecture (described in Chapter 5) across the processing layers and user interface (UI).

The derived ACS framework (Figure IV-10) is focused primarily on incremental implementation of MoHem/CREM with the goal of automated motion assessment/analysis. The main elements of the depicted research activities within the proposed prototype framework (Figure IV-10) are as follows:

- The initial heuristics collection stage is mapped to a targeted assessment skill level (e.g. novice to intermediate);
- The follow-up implementation feasibility stage for the chosen heuristics includes data collection with initial consideration of accuracy, sampling frequency, degree of obtrusiveness and relevant issues drawn from multidisciplinary data analysis;
- Resulting outcomes include individually codified heuristics as assessment components that collectively contribute to a global assessment of an observed motion event. The proposed system architecture (see Chapter 5), including its on-line and off-line processing variations, permit the adding, removal, replacement and amendment of MoHEM/CREM modules, supporting cyclic research and implementation; and
- From the range of possible heuristics, candidates appropriate for automation of an observational model are determined, the most important factors influencing heuristics implementation priority being viewed as: implementation complexity, the coaching scenario (CS) context and the ease of validation.

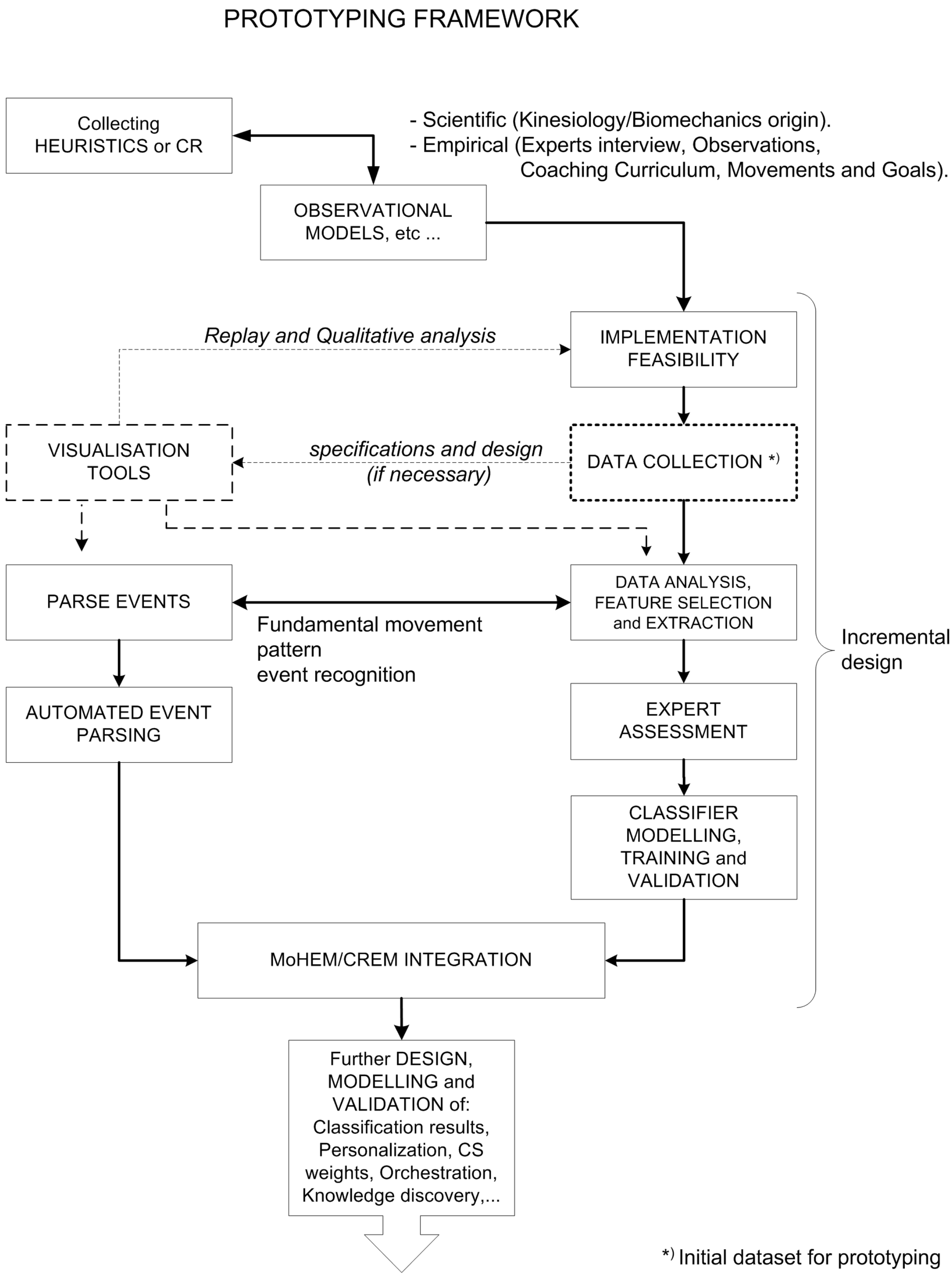


Figure IV-10. Research framework illustrating modular MoHEM/CREM design, combining multi-disciplinary research methodology. The visualisation tools are required for successful data analysis, expert assessment/supervised learning, modelling and overall prototyping stages.

Each MoHEM/CREM functional design originates from either observing an expert's efforts, empirical sources (e.g. indicated by a coach), or from scientific origin (e.g. biomechanics or injury prevention). The need for minimising data dependence in the design of MoHEM/CREM is justified by a desire for modular transferability/reusability across disciplines and the fact that any given target system may have different data restrictions compared to its prototype. A KE approach to machine implementation of heuristics and coaching rules combines utilisation of generic with modular development approaches (as Figure IV-9 utilised in golf case study, Chapter 7 and Figure IV-10 utilised in tennis case study, Chapter 6).

4. Generic Framework for Motion Data Analysis and Modelling

Complementing sporting domain knowledge, the proposed framework (Figure IV-11) for motion data modelling specifies the order of activities and associated analysis methods for machine processing, covering low-level to high-level data processing contexts.

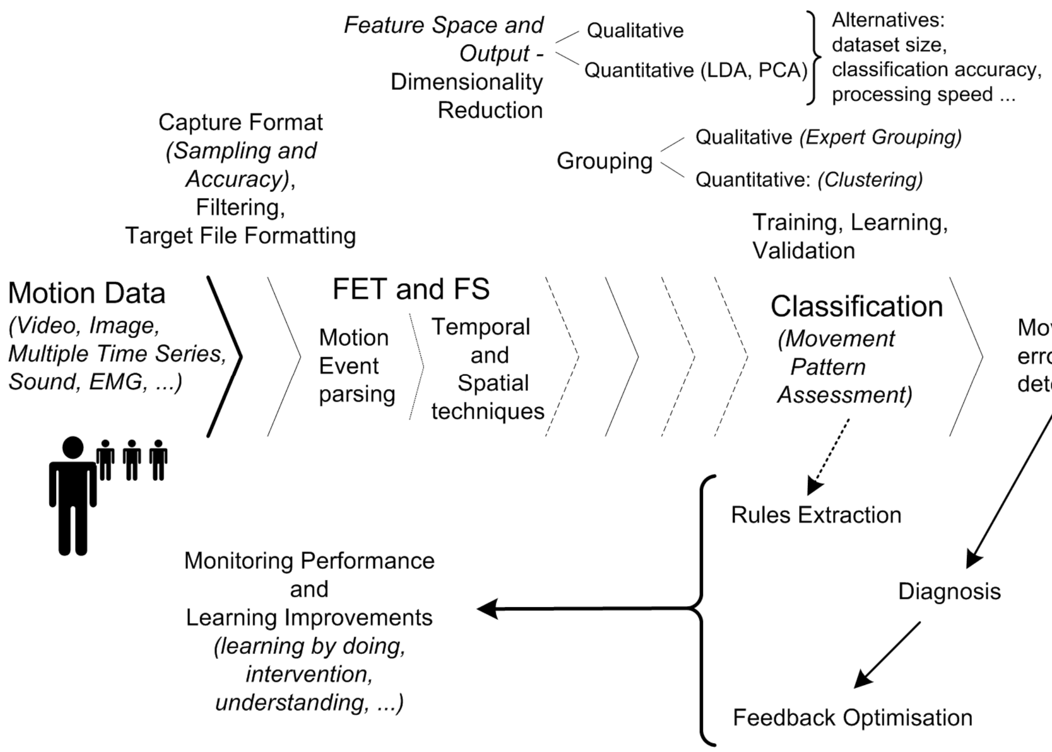


Figure IV-11. Machine Learning (ML) augmented context. Raw motion data is analysed, transformed into ML features, further analysed for classification in diverse information processing contexts.

Knowledge Discovery (KD) may be obtained as a result of extracted classification rules from a validated model on the available data set.

4.1 Motion Data Modelling: Analysis and Transformations

The systematic approach of motion data modelling focused on analysis and transformation – as a conceptual framework – is provided to support the transfer of aspects of qualitative analysis and an augmented coaching process into a machine-based system.

In this thesis, the abstract, qualitative component of human thinking processes underpinning the creation of mathematical transformations of motion data required in *feature extraction techniques* (FET) is perceived as difficult to automate (Figure IV-12 and Figure II-1). For example, the qualitative component includes the domain insights and human descriptive rules influencing inference for a given problem.

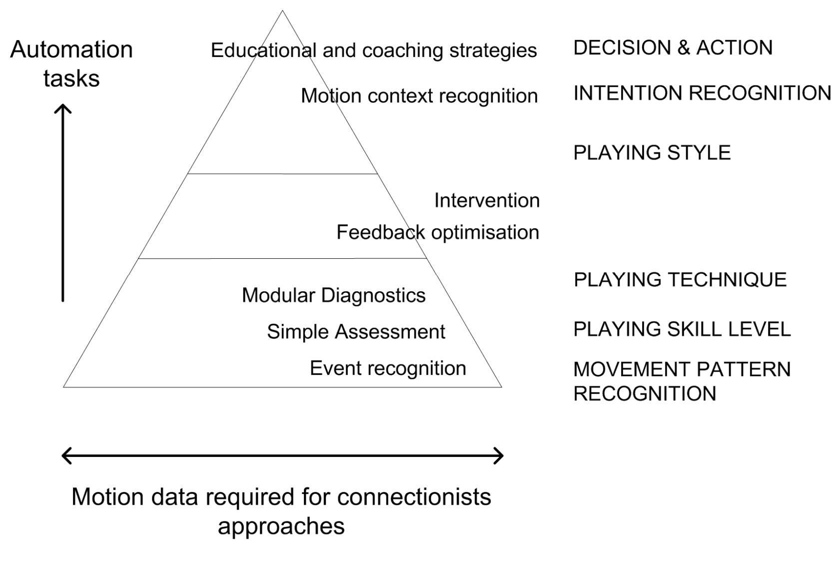


Figure IV-12. Automation tasks in the context of AI and CI and associated data quantities.

Complementing qualitative approaches, the CI discipline with its bases in quantitative epistemology may extend the data analysis to incorporate further feature transformations and evaluation related to selecting features e.g. to identify the feature subset with the most discriminant capabilities for classification from an available feature set (as demonstrated in

Chapter 7). *Feature selection* (FS) in the modelling of an automated processing context may also involve a decision on what are reasonably good classification accuracy levels relative to processing demands. In order to automate aspects of augmented coaching, the processes through which a machine and the human mind perform classification of observed motion data events may not necessarily involve use of the same feature space or decision boundaries (Duch & Grudzinski, 2001; Duch, Setiono, & Zurada, 2004), as demonstrated in Chapter 6. The abstract high-level transferable concepts, cross-disciplinary elements and the conceptual framework linking motion data and modelling strategies emerged from both case studies.

4.2 Taxonomy of the Research Fields and Associated Data Processing

Complementing the investigation of motion acquisition and data pre-processing, this work is also founded on the synergy between: (1) The augmented coaching context and goals of modelling human motion activities; and (2) Possible issues arising in, and the rationale for, the data analysis, pre-processing, preparation and implementation of diverse feature sets for soft computational or other analytical processing of low-level motion data (Figure IV-13).

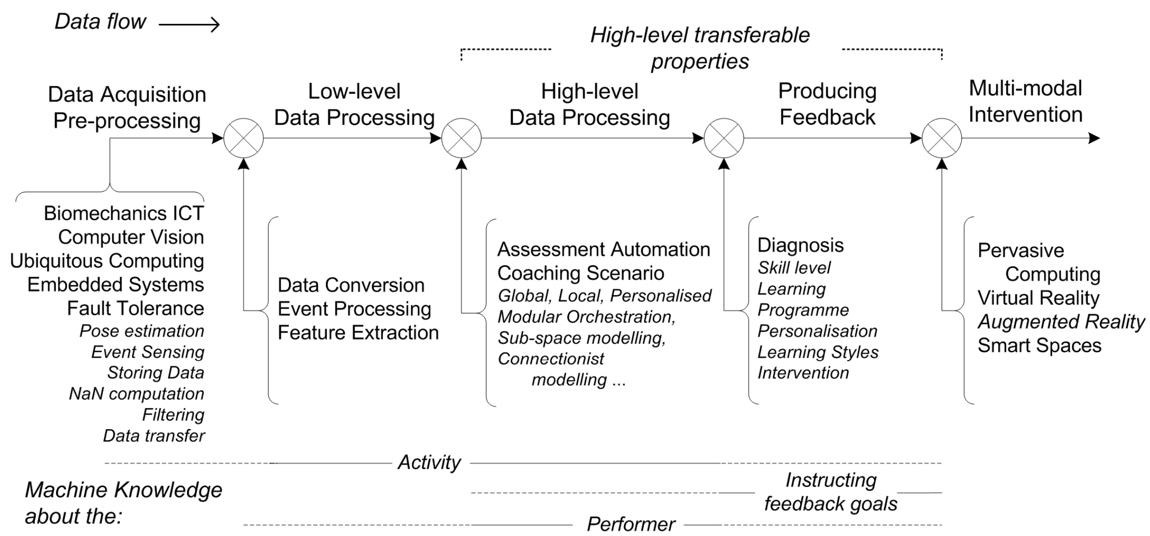


Figure IV-13. Taxonomy of the research fields and topics related to data analysis and modelling of human motion activities.

The 'bottom-up' approach includes an investigation of what is required to produce the isolated and human-comprehensible elements of assessment in the context of motion data processing. Introduced here, the concepts and methodological directions transferable to diverse sport domains are validated over two diverse case studies (Chapters 6 and 7).

4.3 Motion Data Modelling and its Impact on ACS Design

The taxonomy (Figure IV-13) depicts a 'data flow', incorporating both novel and existing concepts, drawing on multiple disciplines involved in distinct processing stages. In each stage, the symbol $\otimes$ indicates a complexity increase combined with the need for more data, previous and additional concepts and modelling requirements.

A key distinction made in this thesis is the separation of *'Low-level'* and *'High-level'* processing and the modelling of the processing stages (Figure IV-13). All stages can be seen as layers of implementation complexity of augmented coaching systems and in the area of (machine-based) knowledge discovery of the activity of a performer.

One of the boundaries of this thesis is the stance that a learning system's output is viewed as feedback. In this thesis feedback is restricted to a diagnosis which is constituted by a set of automated assessments on supplied motion data.

Another boundary related to the implementation and feasibility aspects of the approach is linked to physical data acquisition and motion data format and nature (Figure IV-14). Although the motion capture topic is fundamental to this thesis, it also extends well beyond the scope of this thesis. That said, it is necessary here to consider the issues of motion data capture constraints, pre-processing and implementation as relevant to higher-level motion data processing.

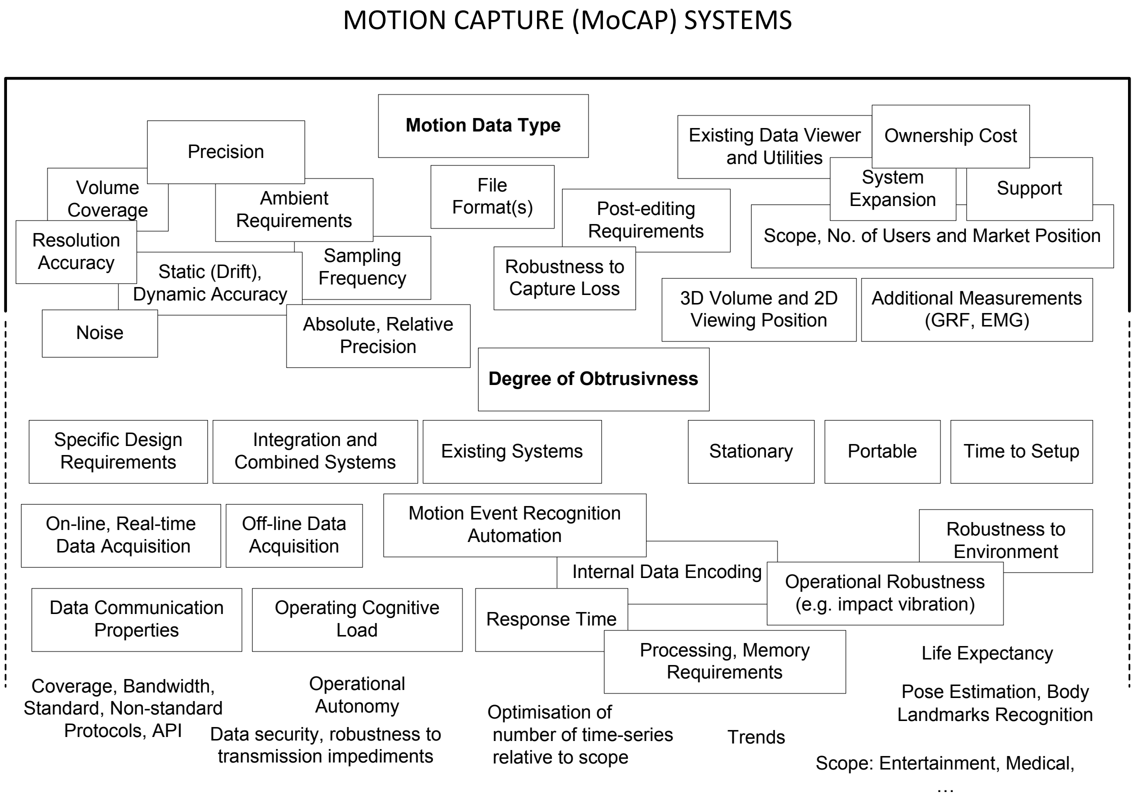


Figure IV-14. Mental model – motion capture systems (MoCap) properties and usability context. The included items are identified taking into account the issues emerging from the case studies for the scope of bridging multiple disciplines relevant to this thesis.

Augmented coaching system design is bounded by restrictions requiring tradeoffs and optimisation of the requirements and properties of a motion capture system, depicted as a mental model in Figure IV-14. Although the elements of the mental map are interconnected, the following two examples illustrate their importance from different perspectives:

- **Motion data type** with precision and sampling frequency is important for modelling motion data and the ability to extend system operation function; and
- **The degree of obtrusiveness** is important for the usability of an augmented coaching system and software engineering discipline.

4.4 The Insights in Transforming a Coaching Process into ACS Design and System Operation

A coaching process (preparation, observation, assessment/diagnosis and feedback/intervention) is typically cyclic in nature. Within each training session, a task and an observation goal may be the same as in a previous cycle (e.g. for incremental improvements), or it may be different (e.g. oriented towards a new coaching goal). Before an exercise a coach would inform the learner about the next task, which could be from the learner's perspective an intervention addressing a prior error/weakness or (re)introducing a new lesson or goal. It may also be a description of expected adherence to a prepared lesson from a learning programme or a step of an exercise plan, working on competitive strengths prepared by a coach. The observation and evaluation that can then occur during the learner's task execution can be considered in terms of diverse criteria. For example, the evaluation criteria for beginners may not include consideration of fine movements but it may focus only on fundamental pattern/skill activity (e.g. large muscle group activity or balance related aspects – stance and weight-transfer relative to action zone). In another CS focused on pressure drill/training, a coach may initially focus their evaluation attention more on foot work and balance and less on the resulting outcome accuracy.

Activity in the preparation stage would involve determining appropriate details for both the CS and management of the experiment e.g. environment considerations, protocol for conducting the experiment, recording the observation, verifying the recording, followed by motion data post editing/pre-processing for low-level processing stage.

4.4.1 Task Challenges

Given the exploratory and cyclic nature of the proposed investigation and framework (Figure IV-9 and Figure IV-10), it is not possible to predict with complete certainty the details of each step of the design and all associated design challenges. In transitioning from the generic framework (Figure IV-9) to the modular design framework (Figure IV-10), the important components of KE/CI are explained further:

- *Knowledge of activity* and data capture – challenges and insights; and
- Feature selection and extraction techniques influencing classification results – strategic design properties.

The Table IV-2 summarises the anticipated tasks and associated challenges of the incremental design paradigm.

Table IV-2. Tasks and challenges summary.

No.	Step	Task	Challenges
1.	**Preparation**	Collect heuristics. Select model for qualitative analysis.	Weighting heuristics relevance and prioritising critical features for skill level. Addressing possible shortcomings, combining or extending model to be suitable for ML. Plan to observe most important CS
2.	**Observation**	Collect data set for modelling.	Experiment setup, instruments, acquisition protocol. Subject concerns. Acquiring representative data set with good generalisation Data analysis and visualisation.
3.	**Evaluation**	Select feature set, feature selection or extraction technique. Select classification algorithm and optimisation. Select event extraction algorithm.	Visualisation for both machine learning and qualitative analysis. Highly discriminative property for categorisation (machine inference). Test most significant first and if necessary to improve add less significant features. Avoiding (where possible) overlap between groups and highly correlated features. Choosing classification algorithm - criteria: evolving, accurate, computational cost, ability to extract rules, learning via rules or data and rules, can knowledge (set of rules) be inserted and extracted?, etc. Choosing validation related to data set size and problem space dimensionality Event extraction criteria: high detection rate vs. false positives

4.4.2 Knowledge of Activity and Data Capture – Challenges and Insights

Imposing a high-level of control over the experimental setup is important for ensuring rigorous data acquisition, observation (Knudson & Morrison, 2002), incremental acquisition (including merging data for further ECOS training) and further modelling as well as reducing potential error components. For example, a part of the coaching instructional video set comprising the video-based augmented golf coaching system ("Leadbetter interactive," 2005) specifies a desired experimental setup, involving camera settings and placement relative to a subject. Associated with the use of 3D retro-reflective markers, issues to be addressed (Chapter 6) include: proximity clearance e.g. causing marker tracks to be swapped; number of markers e.g. the physical requirement for at least three markers per isolated moving segment if internal rotation is important or two for displacement only; markers attached to non-bony landmarks may provide noise component due to muscle and skin volume – tissue movement travelling in a wave-like pattern noticeable at higher frame rates.

It is generally desirable to capture data at higher precision and frequency than is necessary for the target system. This enables incremental model design using the same available data set so that it may be analysed with increasing sophistication as new techniques emerge. The same rationale for incremental model design applies for the use of additional markers or for space reduction of machine features.

4.4.3 Feature Selection and Extraction Techniques Influencing Classification Results – Strategic Design Properties

The abstract mental processes executed by a coach in identifying hypotheses, heuristics, coaching rules and the associated critical features to be used for modelling (Figure IV-15) is not perceived as a linear flow of thoughts that would be relatively easy to automate. For example, a range of possible trade-offs and conflicting design constraints must be considered (Figure IV-16) – as a part of the strategic design process, influencing feature extraction and selection – before modelling a classifier.

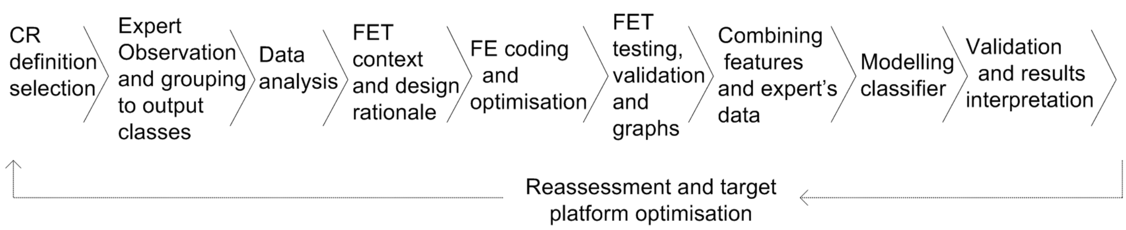


Figure IV-15. Heuristics inspired coaching rules (CR) modelling. Individual or adjacent stages may be subject to reassessment and cyclic improvements.

The machine feature sets associated with a given heuristic or a coaching rule may vary when experimenting with diverse requirements or when considering different design stages such as:

- Proof of concept, hypothesis testing;

- Prototyping;
- Experimental and exploratory design; and
- Target platform design.

4.4.4 Strategic Design Rationale for Feature Extraction Algorithm

Optimising for diverse feature selection and extraction algorithm variations would likely to result in diverse feature sets alternatives – which after being supplied to a classifier, are likely to produce different classification results. Making informed design decisions may lead to knowledge discovery from motion data (see Chapter 6). Surrounding constraints influencing optimal strategic design of feature selection and extraction techniques for different implementation contexts are shown in Figure IV-16.

To achieve optimal classification performance within given circumstances for a target system, ML space reduction is justified with optimisation of surrounding constraints, and strategic design rationale (Figure IV-16).

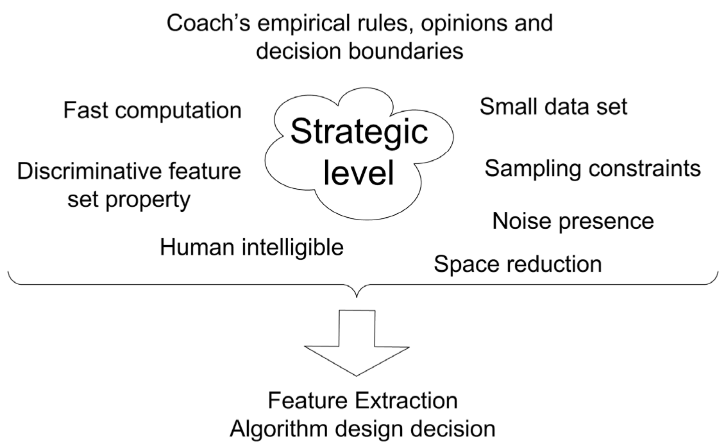


Figure IV-16. Strategic design rationale influenced by surrounding constraints – resulting in problem specific feature extraction algorithm. Implementation variations of algorithm may be considered at early design stage for modification purposes when the circumstances of the context change.

The following insights are intended to illustrate that elements of the prototyping investigation including coach's empirical rules, opinions and decision boundaries are qualitative in nature and evolving i.e. subject to change. Although error diagnostics are less likely to be disputed, the priority of intervention and feedback opinions may be subject to disagreements. The design rationale may be illustrated by the following questions and reflections:

- Can a system provide flexible and personalised assessment?
- A small data set may require investigation whether the available data is representative in relation to the data universe or if the available data set is unbalanced;
- Sampling frequency or accuracy may be too low i.e. may not be suitable to provide data for particular coaching rule assessment automation. With future data becoming incrementally available, is it possible for an algorithm to process motion data captured e.g. at higher frequency without recoding/modifying its algorithm? and
- The qualitative nature of human expert insights and the quantitative representation required for machine knowledge may be similar, or potentially very different e.g. the machine-based representation may become incomprehensible due to high dimensionality, large numbers of complex rules in inference, or general problem space transformation. From an implementation perspective for automated KP diagnostics, a system may be optimised for higher accuracy with results close to those resulting from human expert assessment, or may instead accommodate lesser accuracy while enabling more comprehensive error diagnostics and greater transparency in operation.

A feasibility investigation resulting from data analysis may also include information on distribution of *knowledge of activity* (e.g. from captured context, as reported in the case studies), relative to available motion data.

Sub-space modelling of e.g. a particular activity or a derived feature subset in isolation relative to its surrounding activity and available data may additionally require modelling strategies for unbalanced data set problem areas.

Resulting data distribution analysis (e.g. including distribution of motion events or grouping/clustering information) may influence modelling decisions such as utilisation of novel ML validation and training incident prediction (IV-1) for small or unbalanced data sets.

At a strategic level, the *strategic design rationale* (Figure IV-16) unifies the concepts, mental models and frameworks introduced in this chapter.

4.4.5 Data Analysis: Cluster Distribution and Validation Incident Concerns

For cases in which there is a small data set relative to problem dimensionality or a larger data set containing unbalanced data[11] additional information may be required to determine whether the sampled data set is representative of a larger population data set.

Distribution of *knowledge of activity* (or captured context) for augmented coaching system off-line data may be grouped into clusters indicating the occurrence of a particular activity practice within training or competitive circumstances. Another example of cognitive clustering is similarity grouping analysis by an expert, which may be especially useful for small data sets that utilise information about grouping subjects by similarity (e.g. gender, age, performance).

In the case of machine learning, data analysis may include quantitative analysis e.g. clustering, and investigation of overlapping data classes (as shown in Chapter 7).

Motion data analysis may also be motivated by a desire for inference similarity in system design and modelling i.e. machine and human inference operating on the same or similar feature set with similar decision boundaries; or by experimental rigour to ensure that one or more of the output classes would not incidentally be absent from the testing or training sub-sample portion. The novel pre-processing analytical formula (IV-1) investigated and applied in (Bačić, 2006b; Bacic et al., 2007; Bacic, 2008b) can help an analyst to estimate the probability of such *validation incidents* and also to choose an appropriate cross-validation method and data split ratio.

Event C and the *incidents* cases examples (A, B, D) are defined as:

A … entire cluster selected for testing

B … one sample is selected for training

C … k cluster samples are selected for testing

D … entire cluster selected for training.

[11] E.g. one output class is substantially less represented than other(s).

$$P(C) = \frac{\binom{j}{k}\binom{n-j}{m-k}}{\binom{n}{m}} \qquad \text{(IV-1)}$$

Where:
n … size of the sample space S
S … sample space, $S = \{1,2,\ldots n\}$
j … size of the observed cluster
k … number of samples in test data from observed cluster
m … size of the test data set M
$P(C)$ … probability (of k cluster members randomly selected in test data set).

The application of the formula (IV-1) may be extended to include probability distributions – for example, the probability of *k* samples from a minority class appearing in the test data set – forming as a result Gaussian bell shaped curve, where *k* (samples) is included in a graph as an independent variable (see Chapter 7). The results of such probability distributions can be used to inform decisions such as a choosing validation method and the setting of parameters such as the percentage for holdout validation split ratio or cross-validation fold size. The application of the formula (IV-1) may therefore improve modelling of human motion activity and related problem areas.

Data analysis may indicate if a data set is representative of the expected *data universe* or may provide an estimation of data set size relative to problem space dimensionality. Classification results of a trained classifier may therefore vary, should more test data become available. Therefore for research rigour, post-processing of an optimal classification model analysis may also address the possible existence of *overfitting*. In such cases it is possible to illustrate the difference between *overfitted* and investigated proposed models, so that the classification results can include comparisons with additional sub-optimal models (see Chapter 6) classification results, or an *overfitted* solution can knowingly be investigated (Chapter 7).

4.4.6 Heuristics, Coaching Rules and Modular Assessment Integrative Modelling

In order to exhibit the desired degree of automation in a targeted augmented coaching system, the system should also be able to recognise characteristic activity as motion events and parse motion event data automatically.

Temporal and Spatial Feature Extraction for Motion Sequence Design Pattern

Automated machine assessment of motion data is enabled by autonomous recognition of characteristic motion patterns and associated data transformations of such characteristic motion patterns into machine representative features (Figure IV-17).

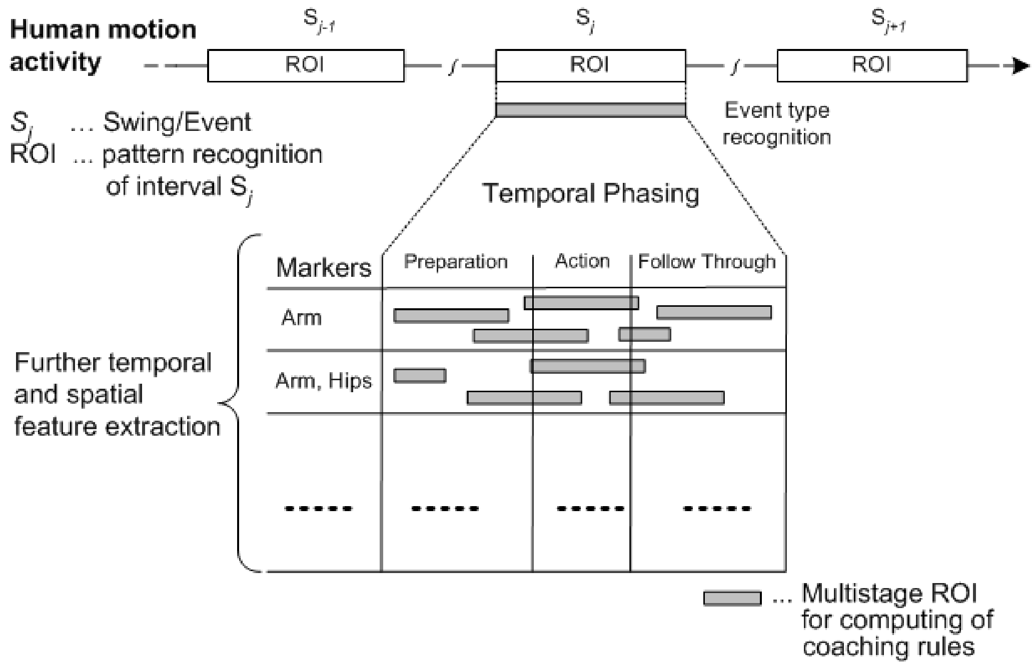


Figure IV-17. Mental model for motion sequence design pattern or generic machine learning data pre-processing based on temporal and spatial concepts. Recognised and extracted motion event S_j is processed further based on multistage temporal and spatial analysis.

The novel motion event (as motion pattern) recognition from multi-time series of motion data is based on identifying a local maximum or a peak of: energy, force, acceleration or velocity of moving parts (body or equipment) of interest, relative to the target line. When a local maximum is detected – typically around the action/impact phase – the next computational step provides start and stop information of a recognised motion event around the detected local maximum. As demonstrated in Chapter 6, both ROI and Feature Extraction may involve temporal and spatial computational techniques.

Modular Assessment

The specific instance represented in Figure IV-18 is an implementation diagram unifying modular ML Assessment rationale (Chapter 3) with experiments addressed in later chapters.

Multistage integration of MoHEM/CREM design and algorithms are described further in Chapter 5.

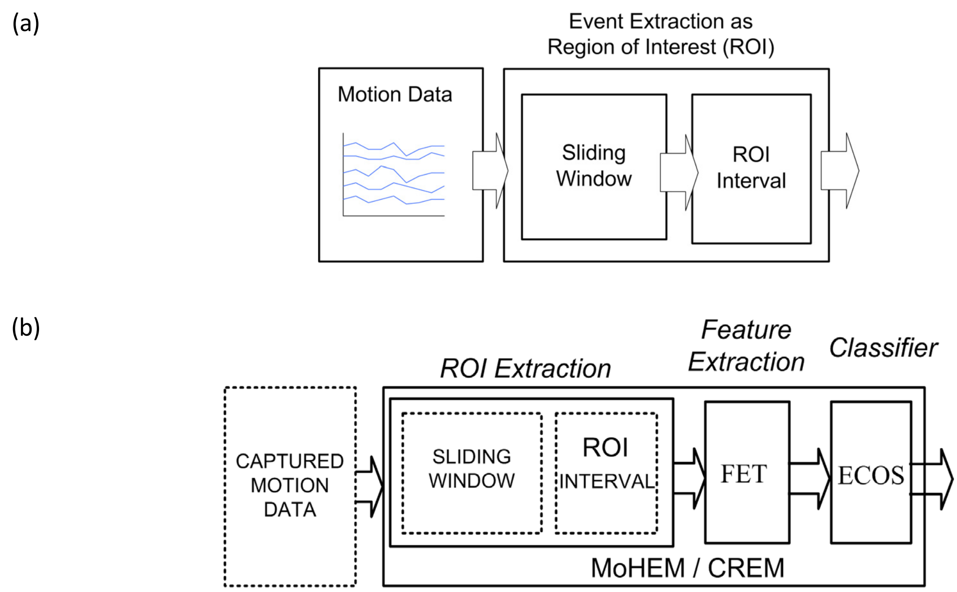


Figure IV-18. Modular motion data processing. (a) Concept of automated motion event filtering. (b) Event filtering, recognition and assessment classification integrated in MoHEM / CREM block diagram. Adapted from (Bacic, 2004).

4.4.7 Prototyping Tasks and Challenges

In parallel to the MoHEM/CREM design, given the goals of the research there is also a need for visualisation software that can show both motion data for qualitative analysis and for modelling activities (Figure IV-10). This visualisation software needs to be provided along with the motion capture equipment e.g. 3D stick figure viewer and supplemented data export capabilities for spreadsheet graphing or similar application; without flexible multi-data format support, visualisation may become a critical challenge or an obstacle at each stage of the framework.

Addressing Visualisation Requirements

> *... video replay can provide important information for the analyst to improve qualitative analysis.*

(Knudson & Morrison, 2002, p. 200)

Within the context of this research, visualisation tools are required: (1) for qualitative data analysis and (2) to support the abstract process of design of appropriate feature extraction techniques (FET). For example, utilising 2D and 3D viewing of motion activities can support the ML implementation of heuristics into features, or the inspecting of a range of correctness for critical features. Visualisation can also enable a degree of validation of the proposed research design steps (as shown, for example, in the design steps underlying the case study in Chapter 6). The necessity of observational rigour, qualitative analysis of motion replays and planning for vantage points were introduced in Chapter 2. From a modelling perspective, the availability of visualisation tools eliminates or reduces the cognitive load on the analyst/coach, allowing their mental focus to shift to design issues e.g. abstracting the problem associated with FET tasks. In addition to 2D and 3D motion data viewing, animation capabilities enable the analysis and visual inspection of both spatial and temporal events (motion sequences). Accurate animation and interaction control, the ability of a user to replay a particular sequence (A-B repeat) at different speeds (e.g. real-time, slow motion), step-by step operation, zoom in/out and file access management are amongst the most desirable usability functions of motion data viewing and qualitative assessments. It is expected that some of the visualisation tools may be designed[12] and further reutilised as components for other practical applicative software deployments.

Data Collection Challenges

> ***Kinect …***
>
> ***This "natural interface" will really amaze people over the next decade, we will just take it for granted, that's very big, and that along with robotics and understanding the diseases …***

Bill Gates, Philanthropist, the founder of Microsoft.
Referring to Kinect, as "natural interface" (Retrieved 10 Nov. 2010, from www.youtube.com/watch?v=xDngQ4WV2ec)

[12] That may also include developing layered and replaceable/reusable "building blocks" architecture and proprietary libraries for the purpose of stand-alone deployment, portability or for independence of the third party's (installed) software.

Data collection, unquestionably a broad topic, is considered here as providing a surrounding context to the central scope of this thesis. Identified important questions regarding data collection relevant to ACS development (Figure IV-14) are as follows:

1. What are the degrees of obtrusiveness, resolution, sampling frequency and accuracy required for a prototype and how might they differ from those in a target system?
2. What are the restrictive properties of a motion capture system regarding, for example: on-line and off-line processing; low-level captured data pre-processing; motion data formats; bandwidth restrictions; and availability of supporting tools and libraries for integration with other software?
3. To what degree could the outcomes from the experiments (case studies, Chapters 6 and 7) be generalised for future applicability and cross-disciplinary use with other motion capture systems?

5. Chapter Conclusion

This chapter has introduced a novel generic ACS framework and a particular instantiation associated with a modular approach, proposed to support error detection in the qualitative assessment of human motion, in a similar manner to human reasoning.

Building on the concepts and challenges introduced here, the next chapter focuses on generic application aspects of augmented coaching automation and implementation of those into a system.

Chapter 5

V. NOVEL CONNECTIONIST METHODS FOR MODELLING AND ANALYSIS OF HUMAN MOTION: SYSTEM AND ARCHITECTURE

Continuing from the previous chapter, this chapter presents general methods, implementations and development aspects of an augmented coaching system.

The architecture and associated methods introduced here are aimed to address practical key aspects of ACS automation: (1) Incremental development of motion assessment capabilities relying on evolving machine learning; (2) Processing task separation to an n-tier architecture; (3) User profiles, tasks and interactive requirements; and (4) Diagnostics as human-intelligible itemised assessment feedback.

Central this chapter are the examples of motion data transformations to machine features (as implemented in back-end processing with other CI methods), which are tested, integrated and validated in the first case study (Chapter 6). The included algorithms are based on low-level, raw, 3D multi-time series motion data sampled at regular time intervals – representing movements of characteristic points of the body. The same is true for data in the algorithms supporting visualisation required for modelling, analysis and other user tasks.

1. System and Architecture

The prototype system development described here is intended to support the novel inter-disciplinary concepts, research and modelling requirements identified in prior chapters, and to provide a tool to enable the validation of case scenarios of automated motion assessment modelling.

1.1 Multi-discipline Background

In addressing relevant aspects of the human computer interaction (HCI) discipline, this chapter reports on the prototype architecture and its application usability for multiple user profiles, supporting the main scope of the thesis. The development leverages software engineering principles including software reusability, portability and implementation of open, non-proprietary standards. The key areas of kinesiology and CI/KE are supported by the software engineering discipline in terms of prototype development to support qualitative analysis and connectionist modelling of the same motion data set. Hence, the prototype system's user interface should unify and functionally support three major multi-discipline tasks:

1. Incremental functional and modular development of automated assessment capabilities relying on connectionist and other CI approaches with minimal changes to the user interface.
2. Qualitative assessment validation and experimental rigour for motion data modelling.
3. Learning and coaching educational activities.

1.2 ACS Prototype: Concepts and Components

The main concepts and associated interactive tasks for an ACS includes: training and validation of connectionist-based modules; flexible assessment criteria (via sub-space modelling, CR orchestration, machine knowledge extraction/insertion); and expert assessment via replay of motion data. The general capabilities are illustrated using 3D tennis motion data and coaching rules – linked to the case study that follows in Chapter 6.

1.2.1 Prototyping Architecture with Front-end User Interaction and Visualisation Aspects

The multi-tiered architecture of the prototype (Figure V-1) consists of the three parts:

1. The computation server (back-end COM server) is responsible for data exchange with the front-end client and computations of all ML algorithms. As such, it allows

direct interpretation of MATLAB™ code and function libraries (e.g. external data access, feature processing, classification tasks and learning architecture (Figure IV-8) implementation).

2. The front-end client is responsible for user interaction via the graphical user interface (GUI), presentation logic and session management with the back-end computation server and the 3D viewer. Session management ensures maintaining state in *singleton* operation of the 3D viewer and MATLAB™ COM Server.
3. The 3D viewer (developed specifically to support this research) is responsible for animated 3D stick figure screen representation, user interaction and data exchange with the front-end client. While session management ensures *singleton* viewing of the currently assessed motion event, for multiple event viewing (e.g. to enable similarity grouping and/or comparisons) there are also available variations of the 3D viewer operating mode. Specific to 3D data, functionality includes interactive[13] virtual camera view (angle, position and zoom), playing and recording a replayed animation sequence as a set of viewed images. The *Play* function includes step-by-step viewing, variable play speed, loop and file play list. Similarity grouping operation (using multiple stand-alone 3D viewers) includes interactive preset and persistent virtual camera view settings with drag-and-drop of desired 3D motion data files, to ensure identical viewing angles.

The main benefit of the layered approach (Figure V-1) is that it results in a reusable and replaceable (modular and layered) architecture, where each layer can be modified or upgraded within its own specific operation, with minimal or no changes required for the rest of the system. For example, the 3D Viewer layers ('Animation', 'Camera View', and '3D to 2D View') can be replaced with a generic media player abstraction layer supporting a variety of input media formats (as *plug-ins*). For interoperability between different software and tools, the common commands for interactive 3D or video replay, event communication, synchronisation and initialisation parameters can be achieved by using *external synchronisation for visualisation and replay*.

Other than the benefits of bounded testing and debugging, within each layer, with new connectionist models being invented, these new models can be incrementally added to

[13] Similar to video games, camera view can be changed via keys and mouse during static frame or playback. Appendix B shows resulting 3D views and reference planes.

improve the system (in accuracy, performance) and to broaden its set of available assessment modules.

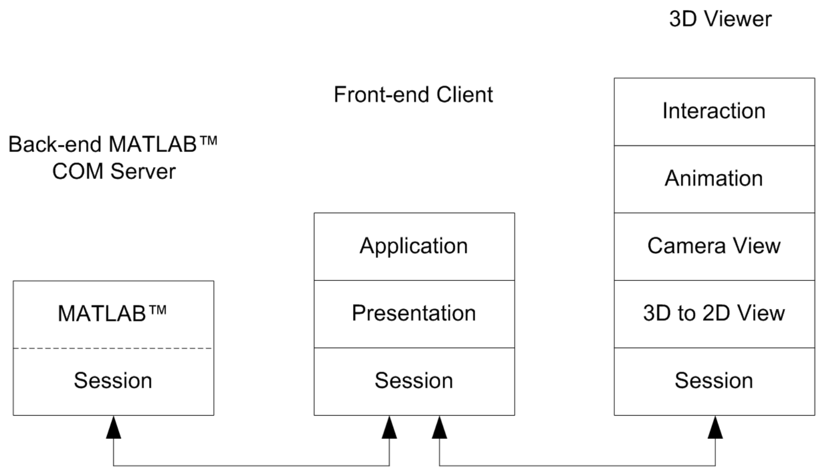


Figure V-1. Layered computational architecture enabling prototype operation and task separation.

1.2.2 Learning System Architecture as Back-end Prototyping

Practical implementation of on-line and off-line processing functionality can also be achieved through variations of the learning system architecture (see Figure IV-8) e.g. as a prototyping instance for racquet sports in Figure V-2.

The key benefit of this architecture (Figure V-2) is that it can be implemented as per the initial design, upgraded if needed and integrated into an incrementally more complex parallel architecture. Such variation is suitable for prototyping stages in the incremental modular design as shown in (see Figure IV-10). Without having to rely on automated enabling/disabling of modules and/or during prototype (or a MoHEM/CREM) development, a developer may start by manually extracting temporal ROI and assigning an identification number to a characteristic motion event – which as an added feature – results in one extra dimensional increase of the feature space. As a separate task, the 'Rule module selector' (see Figure IV-8) intended to recognise a set of possible characteristic events is likely to be implemented later in development, in contrast to initial FET. 'Event Extraction' as swing parsing (Figure V-2) may also be included in CREM as 'Swing Recognition' – a ROI filtering function (see the algorithm in Table V-3).

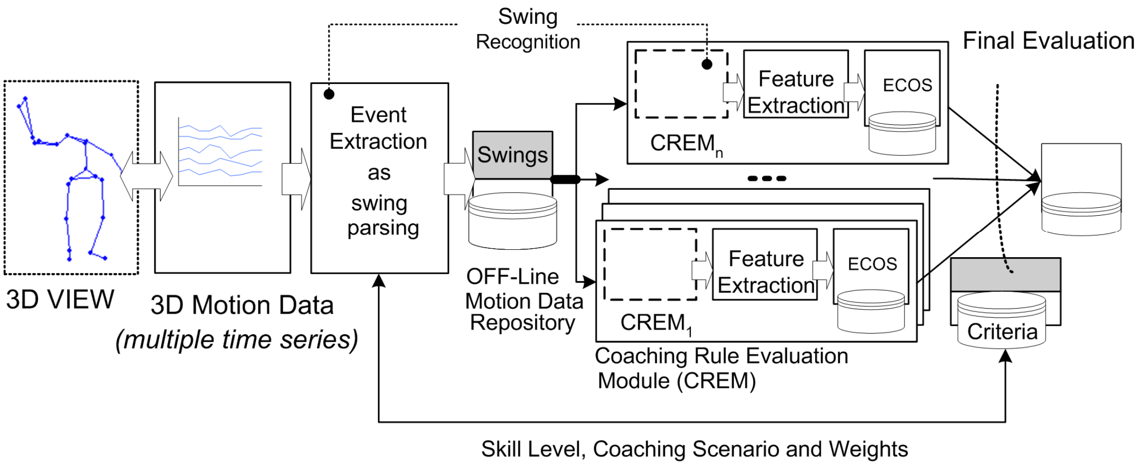


Figure V-2. On-line and off-line prototyping learning system architecture modification for modelling framework applicable to racquet sports (Chapter 6).

The machine knowledge created (i.e. extracted from the ECOS classifier) for each MoHEM/CREM along with the associated criteria can be structured into a database in relation to a specific analysis instance: as an individual coach, personalised trainee, skill level profile, coaching scenario (Table V-1), or as a contribution to global machine knowledge.

1.2.3 Subspace Modelling and Module Orchestration as Weighted Selection of Collective Assessment

Subspace modelling and *orchestration* as a form of augmented coaching supporting training of targeted or specific skills is related to concepts of optimisation of a coaching scenario (CS) (see Figure IV-5).

The orchestration concept that leverages a modular design in this thesis is implemented via weighted assessment criteria (Figure V-3). Weighted assessment may correspond to a CS for global, group or personal idiosyncrasies such as skill level. Ultimately, augmented coaching support systems should be designed to adapt their behaviour depending on a coach's intentions in given set of circumstances.

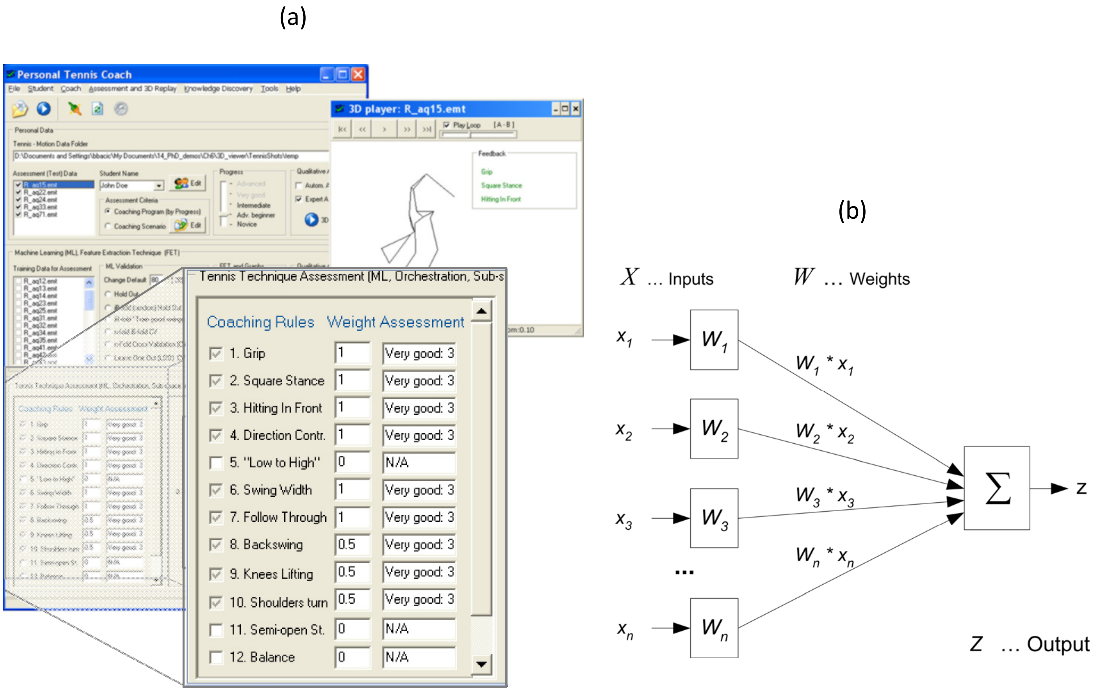


Figure V-3. Weighted selection of collective assessment modules. (a) Modifying weighted selection of coaching rules via GUI. (b) Back-end weighted computation of collective assessment of CREM processing supplied as inputs X.

The incremental formula (V-1) (as introduced earlier in relation to the orchestration concept) enables the scalable and collective assessment operation z of CREM modules $i \in \{1...n\}$. For an end-user, the weights vector W can be normalised to interval [0…1] or assigned as a percentage or to an interval of any preference.

$$z = \frac{\sum_{i=1}^{n}(W_i \cdot x_i)}{\sum_{i=1}^{n} W_i} \qquad \text{(V-1)}$$

Where:

z … common assessment as orchestrated operation of CREM modules

x_i … output of the CREM module with index *i*, where $i \in \{1...n\}$

W … weights vector or matrix matching skill level or programme level.

1.2.4 Matching Skill Level and Programme Level

The benefit of using a simple evolving weighted orchestration formula (V-1) is that its weight configuration is transparent to an end-user. Rather than relying on more complex topological structures or neural network ensemble variations, or other possible connectionist orchestration principles proposed in (Bacic & Zhang, 2004), in this prototype an end-user can at any point re-evaluate and refine the final assessment criterion by manual modification of weights. The other benefits of 'glass box' transparent design principles are in:

- its similarity to human thinking which involves error assessment and the concept of diagnosis based on individually assessed elements and their importance;
- modelling machine-based assessment with inclusion of small data sets containing matching motion patterns to be assessed with flexible skill level and diverse assessment criteria; and
- simplicity, which is important for given thesis' multiple context, as well as visibility of ACS inter-disciplinary aspects, extendibility, adaptability and explanatory power.

Table V-1. Skill level and coaching scenario (CS) coded as two-dimensional weights matrix (in grey). Diverse coaches may create diverse CS and assessment criteria. A matrix column represents weights *W* supplied in formula (V-1).

	Skill-level progress				***Coaching Scenario (CS)***		
Coaching Rule (CR)	Novice	Adv. Beginner	Inter-mediate	…	# 1.	…	# m.
CR #1	1	1	1	…	0.7	…	1
CR #2	1	0.7	0.5		0		0.2
…	…	…	…		…		…
CR #n	0	0.5	0.7	…	0	…	0.8

2. Feature Extraction Techniques Linked to Back-end Modelling and Implementation

The algorithms include generic examples of motion event recognition based on temporal and spatial concepts with derived examples of: (1) impact zone and motion data transformation, and (2) stance (body posture) computation. Specific applications of the algorithms from this chapter and their validation are reported in the tennis case study (Chapter 6).

2.1 Motion Sequence Design Pattern: Temporal and Spatial Feature Extraction

A generic approach for motion pattern recognition, the temporal and spatial feature extraction technique (from multi-time series) for motion event recognition and *coaching rule* modelling, is described as a functional composition (V-2) of the following filtering stages:

$$f_T S_j \circ f_T Sr_j \circ f_T CR_i \circ f_S CR_i \,;\; i, j \in \mathrm{N} \qquad \text{(V-2)}$$

Where for each coaching rule FET functional steps are:

- i ... coaching rule number
- j ... current motion event index
- $f_T S_j$ ... temporal motion event extraction filtering
- $f_{TS} Sr_j$ ... temporal and spatial swing recognition – as a motion event indexing and recognition
- $f_T CR_i$ ... temporal coaching rule region of interest
- $f_S CR_i$ ... spatial computation within the region of interest.

The generic multistage ROI computing of coaching rules – a design pattern integral to MoHEM/CREMs – is based on the design described in Table V-2.

Table V-2. Motion sequence design pattern: Temporal and spatial multistage computation for dynamic and static region of interest.

Multistage dynamic and static ROI
1: WHILE Motion event type recognition (from observed motion activity) DO
2: Sliding Window – to detect local maximum
3: Determining ROI Interval *Sj*
// Dynamic and static CR focus: Within a ROI interval *Sj* – further temporal and spatial ROI
4: Event recognition (e.g. swing type in racquet sports, Table V-3)
5: REPEAT
6: Sub-event separation, ROI interval [*ROIstart, ROIend*]
7: Computing spatial ROI
8: UNTIL the last functional composition as in equation (V-2)
9: END WHILE

Human motion activity is shown (see Figure IV-17) as a series of motion events S_j occurring at random times. The 3D motion data set U is represented here as multiple time series of M markers' positions in three dimensional *(x,y,z)* coordinates – as in equations (V-3).

$$S_j \subseteq U\,;\;\; S_j = \{M(t)\mid t_0 \le t \le t_{k-1}\}$$
$$m_i = (x_i, y_i, z_i)$$
$$m_i(t) = (x_i(t),\, y_i(t),\, z_i(t)) \qquad \text{(V-3)}$$
$$m_i \in M,\quad i = 1,\ldots,n\,;\;\; M = (m_1,\, m_2,\ldots,\, m_n)$$
$$i, j, n \in \mathrm{N}\,.$$

Typically, as is common in biomechanics, the markers would be positioned around selected anatomical landmarks and sport equipment. Marker topology information is then used to create an animated *stick figure* model, representing the captured human body movements (coupled with relevant equipment of interest). Name-labels assigned to each marker would typically represent location as an abbreviated mnemonic (e.g. in descriptive form PSHD … 'Playing Side Hand' or as more accurate PSGT … 'Playing Side Great Trochanter' bony landmark). Where possible, this same convention should be used in algorithm documentation.

For example, in racquet/bat sports' event recognition (Table V-2 – line no. 4:) or $f_{TS}Sr_j$ (V-2) there are common swing types known as 'forehand' and 'backhand'. Having available 3D hip markers and hand information, the novel, generic algorithm can be used to determine a swing type (Table V-3).

Table V-3. Swing type recognition for racquet sports 3D motion event data.

Swing type recognition
Initialise parameters and read filtered input data as a stroke (S_j)
$S_j = \{M(t)\mid t \in \{1\ldots lastFrame\}, M \in \{PSGT, SSGT, PSHD\}\}$ also noted as:
S_j[1...*LastFrame; PSGT, SSGT, PSHD*]
determine a frame number *iFrame* of the local stroke S_j [1...*LastFrame*; *PSHD*] as maximum scalar distance fmax() towards the estimated target projections *ValuesX*:
iFrame←fmax(*ValuesX* [1...*LastFrame; PSHD*])
determine the shortest distance between the *PSHD* and hip markers [*PSGT, SSGT*] as:
IF *ValuesX* [*iFrame*; *PSGT*] < *ValuesX* [*iFrame*; *SSGT*] THEN
near_rear_hipMarker ← *PSGT*
Swing ← *FOREHAND*
ELSE
near_rear_hipMarker ← *SSGT*
Swing ← *BACKHAND;*
END IF
RETURN (*Swing, near_rear_hipMarker*)

Where:
PSGT ... hip marker – playing hand (holding a racquet or a bat) side great Trochanter[14]
SSGT ... hip marker – non-playing hand side great Trochanter
PSHD ... playing hand wrist marker.

Note:
Either one of the hip markers (*PSGT*, *SSGT*) could be labelled as *near_rear_hipMarker*. The algorithm it is not designed to recognise characteristic patterns for all possible swings (e.g. serve, smash, swing between legs, recovery from lob or passing shot attempts).

Inherent to ROI extraction analysis, modelling and algorithm development is a characteristic motion event recognition capability that functions as a shot selector. A shot selector module may be functionally extended to activate assessment modules responsible for rule-based assessment (see also: 'Rule Module Selector' in Figure IV-8). Alternatively a swing or shot selector/recognition function may be implemented in parallel module operation.

2.2 Example 1 – Event Extraction and Indexing Automation

As introduced in Chapter 2, existing approaches for event extraction in augmented coaching systems utilise captured sound filtering and/or detection of impact vibration. The rationale for an alternative approach, and its instantiation in algorithms (Bacic, 2004), is based on insights drawn from energy preservation and movement efficiency in nature – leading to the concept of measuring maximum velocity around the expected impact zone.

In phase one of the event extraction process (Table V-4), incoming data are processed in successive windows using approximately regular intervals of e.g. one second. Within each window, the system evaluates the possible presence of a motion event S_j (see Figure IV-17).

The heuristic rule for detecting motion events S_j relies on two mutually dependent parameters:

- relative stroke magnitude (i.e. local stroke maximum) – a descriptor insensitive to a player's absolute displacement (i.e. position) and
- swing/kick velocity orientation relative to the target line.

If both conditions of phase one are met for a given sliding window W_i then the phase two computation is invoked.

[14] Bony landmark in pelvis region.

Table V-4. Phase I: Sliding window approach algorithm.

Phase_one: Sliding window sequence
1: Initialise parameters and read input data
2: WHILE more input windows left DO
3: update W_i data structure
4: calculate *local_stroke_maximum*
5: calculate maximum *end_velocity*
6: IF (*end_velocity* > *velocity_threshold*) AND (*local_stroke_maximum* > *stroke_magnitude_threshold*) THEN
7: invoke Phase_two(W_i)
8: END IF
9: END WHILE

Where:

local_stroke_maximum	…calculated peak of e.g. velocity relative to target line
end_velocity	…velocity at impact/release surface or points (e.g. badminton racquet – string bed impact surface)
velocity_threshold	…a threshold parameter for Phase_two() invocation
stroke_magnitude_threshold	…a global threshold parameter for Phase_two() invocation.

When invoking the phase two process (Table V-5), to ensure that the entire ROI pattern is passed, the sliding window data interval W_i is extended to include the prior and post window neighbours e.g. $W_i=(W_{i-1},W_i,W_{i+1})$. Variation of the generic algorithm (as done in Chapter 6) can in addition detect and compute other characteristics within the motion event.

Table V-5. Phase II: Determining ROI interval – generic approach.

Phase_two(input_Window): Determining ROI interval
1: Initialise parameters and read 'input_Window' data as W_i
2: determine a frame number of local stroke maximum as $Lmax_j$
3: WHILE ROI_j interval not computed DO
4: reduce frame number
// focus on motion event heuristic/coaching rule:
5: determine $ROIend_j$ frame number
6: determine $ROIstart_j$ frame number
7: END WHILE
8: RETURN ($ROIstart_j$, $ROIend_j$)

Desired properties of the event extraction process that can be measured and validated are the accuracy of event detection and the processing time. Furthermore, one may be traded off against the other depending on relative priority e.g. for on-line detection in real-time it may be desired that the algorithm's properties are optimised in the following order: detection speed, detection accuracy, with preferred missing events over false positive detection.

2.3 Example 2 – Feature Extraction and the Insights Focused on Action/Impact Zone

From this thesis' perspective, a connectionist approach to the impact zone computation (see Figure IV-1) can be generalised into applications related to throwing, kicking, hitting or swinging (the latter being the narrow time segment before a release/impact). In motor skill learning, as we progress from a beginner towards more advanced skill levels, we also develop *kinesthetic proprioception* including cognitive focus for impact/action – 'feel' – that is hard to define in terms of heuristics or coaching rules.

> ***A coach can teach many things, but they cannot teach feel, that is something you must master on your own.***

Nick Bollettieri – an insight from a tennis coach

The original hypothesis underlying the 'feel' modelling approach (Bacic, 2003a) postulated that it is possible for motion data captured with high precision and sampling rate around the action/impact zone to be utilised for machine based assessment into simple categories e.g. ('good', bad').

General heuristics and insights related to the algorithm's design are as follows: from temporal segmentation of the whole movement (see Figure IV-1) it is the narrowest zone delivering highest velocity relative to the target line.

Aspects of the Algorithm

When replacing sampled motion data around the action/impact zone with an approximation formula (for machine learning purposes) it is expected that only one local extreme (min or max) will be evident per plane – during the estimated duration of the impact zone. For example, to approximate captured movement of a point over time, with second polynomial, as in a two-dimensional space there would be three parameters i.e. polynomial coefficients required: p_0 , p_1 and p_2 (see equation (V-4), below).

$$f(t) = p_n t^n + p_{n-1} t^{n-1} + .. + p_1 t + p_0 \tag{V-4}$$

Where:
n … is the polynomial order and
p … are the coefficients.

Although challenging for human comprehension, the polynomial coefficients representing the approximation of a movement trajectory segment can be used as a set of machine features (as demonstrated in the case studies that follow). It is expected that classifications of diverse execution techniques will be candidates for global machine classification of previously unseen execution techniques into simple categories such as ('good','bad'). As such, in this thesis, this approach is also considered as the best machine equivalent for a human-like holistic approach to qualitative analysis.

In addition, there is value in the approach in respect of noise and noise filtering – interpolation of the second degree polynomial acts as a noise filter on converted motion data segments. The implication of inherent noise filtering is that it allows strategic design for inputs from motion capture systems of lower accuracy and sampling rate, without additional computation. The second implication (related to strategic design Figure IV-16) of utilising an interpolation algorithm is the possibility of adding more incremental data captured utilising a different sampling frequency, without the need to modify the code.

With the ability to capture motion data with high precision and frequency it is possible for a machine to process motion data resulting in a machine-based analysis equivalent to a human's perception of 'feel' around the action/impact zone for e.g. the speed and spin components of a moving projectile or in ball rebound.

The spin component $Spin = Motion \cdot \sin(\alpha)$ is introduced by not having an impact or release[15] action intended to maximise projectile velocity to the target line $velocity = Motion \cdot \cos(\alpha)$. As a result, absolute motion velocity (scalar value) at

[15] E.g. 'elastic fingers' release action on a ball at the end of a kinematic chain.

impact/release is divided into two components, rotational and directional (as depicted in Figure V-4).

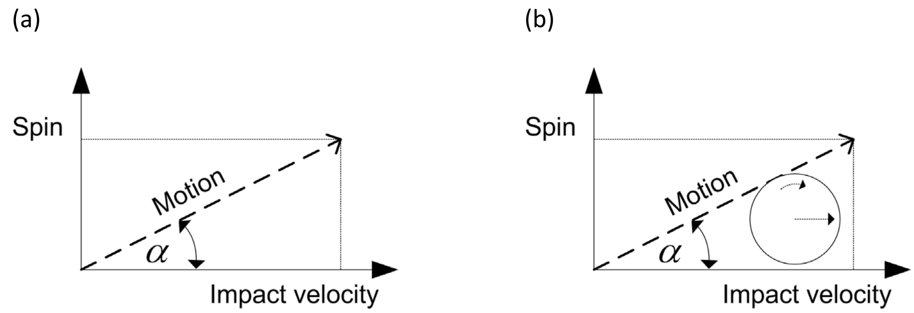


Figure V-4. Two-dimensional motion vector (x,y) translating into spin and velocity components. (a) The angle α indicates impact or release angle relative to the target line. (b) Rotational and directional energy component passed to an object, typically a ball at the impact or release.

Important to connectionist approaches is that if parameters such as relative elasticity response to force, rebound factor, contact surface gripping and rotational mass distribution can be categorised, then it is possible to build a predictor model, based on spin and impact components. For a coaching scenario, a coach may look for presence of a deliberate motion (e.g. 'low-to-high' cue in Chapter 6), when learners learn by active practice the required 'feel' i.e. to control the spin in a similar fashion to that modelled in a connectionist system.

2.4 Example 3 – Stance as Static or Dynamic Feature

A performer's/player's stance can be numerically expressed or computed as an angle between the feet and the target line. In some sports the 'stance' may also include more holistic angular positions of specific body parts (e.g. a set of characteristic stances in traditional karate kata) and balance transfer commencing before and after a recognisable motion event. The stance may be *statically* maintained throughout the motion event in some sports (e.g. snooker, archery), while in others stance may *dynamically* vary through the (swing) phases (e.g. boxing, badminton). Combined with characteristic motion event recognition and indexing, a coach may establish a range of correct stance angles for a given CS criterion.

A feature extraction algorithm expressing a stance angle in racquet sports (Table V-6) is applicable to sampled motion data for a right handed coordinate system (see Appendix B).

Table V-6. Stance angle feature extraction.

Stance as dynamic body position relative to the target line

1: Initialise parameters and read filtered input data as a characteristic motion event (Sr_j)
$Sr_j = \{M(t) \mid t \in \{1 \dots lastFrame\}, M \in \{M_1 \dots M_{last}\}\}$
 	
// Step #1. Optional 3D motion event (Sr_j) stance angle compensation (see Appendix B)
2: Rotate markers' data around *y-axis* to offset *x-axis* to be parallel to the intended target line.
$\forall M = rotate(\{\overrightarrow{Xm}, \overrightarrow{Ym}, \overrightarrow{Zm}\}, \delta)$
3: *Event* ← Swing Type Recognition (Sr_j) – see the algorithm (Table V-3), where:
Event $\in$ { *Swing, near_rear_hipMarker* }
 	
// Step #2. Calculate body centre as virtual marker PelvisC_GT the Step #3.
4: $\mathrm{PelvisC\_GT} \in \{\overrightarrow{Xbody\_centre}, \overrightarrow{Ybody\_centre}, \overrightarrow{Zbody\_centre}\}$
 	
where:
$\overrightarrow{Xbody\_centre} \leftarrow \frac{\lvert \overrightarrow{Xssgt} - \overrightarrow{Xpsgt} \rvert}{2} + \begin{cases} \overrightarrow{Xssgt}, \overrightarrow{Xssgt} < \overrightarrow{Xpsgt} \\ \overrightarrow{Xpsgt}, \overrightarrow{Xssgt} > \overrightarrow{Xpsgt} \end{cases}$
 	
// Step #3. Next stage of temporal ROI filtering – (Figure IV-17 and equation (V-2))
5: Extract Temporal Region Of Interest S_j [*startFrame*...*endFrame*; *PelvisC_GT*], where:
$St_j \equiv ROI(f_T CR_i); St_j \subset Sr_j$
$St_j = \{M(i) \mid startFrame \le i \le endFrame\}$
6: Calculate relative stroke displacement $\overrightarrow{Xstroke\_displacement}$ between the centre of the player's body as virtual marker 'Body Centre' and a player's wrist marker *PSH* relative the target as:
$\overrightarrow{Xstroke\_displacement} \leftarrow \overrightarrow{Xpshd} - \overrightarrow{Xbody\_centre}$
 	
// Determine the Start and End interval:
7: *startFrame* as a frame number ← $\max(\overrightarrow{Xstroke\_displacement})$ of the stroke Sr_j [1...*lastFrame*] at maximum displacement
8: *endFrame* as a frame number ← $\min(\overrightarrow{Xstroke\_displacement})$ of the stroke Sr_j [1...*lastFrame*] at minimum displacement
 	
// Step #4. Further Temporal and Spatial filtering
// $Sttr_j \equiv ROI(f_S CR_i) \circ ROI(f_T CR_i); Sttr \subseteq St_j \subset Sr_j$ – also see equation (V-2)
9: $Sttr_j = \{M(i) \mid newStartFrame \le i \le newEndFrame\}$
 	
// Determine a frame within [*startFrame, endFrame*] interval, in which hand marker
// *PSHD* orthogonally towards the target passes *Near_front_hipM* marker as *newEndFrame*
10: Determine distance vector as $\overrightarrow{h\_dist} \leftarrow \lvert \overrightarrow{Xnear\_front\_hipM} - \overrightarrow{Xpshd} \rvert$
11: *newEndFrame* ← $\min(\overrightarrow{h\_dist})$
12: *newStartFrame* ← *startFrame*

Stance as dynamic body position relative to the target line

13: $no\_of\_frames \leftarrow newEndFrame - newStartFrame$

// Step #5. Final Temporal and Spatial filtering – see equation (V-2):
// Calculate average angle as stance angle α between weight-transfer-moving-feet individual
// markers *PSM, SSM* positions in transverse plane
// $\{\overrightarrow{Zssm}[i], \overrightarrow{Xssm}[i], \{\overrightarrow{Zpsm}[i], \overrightarrow{Xpsm}[i]\}\}$, $\{\forall i \in \Im \mid newStartFrame \le i \le newEndFrame\}$
// and referenced target line:

14: $$\alpha \leftarrow transf\left(\frac{\sum_{i=newStartFrame}^{newEndFrame} \arctan\left(\frac{\overrightarrow{Zssm}[i] - \overrightarrow{Zpsm}[i]}{\overrightarrow{Xssm}[i] - \overrightarrow{Xpsm})[i]} \right)}{no\_of\_frames} \right)$$

where
transf() function is further transforming the angles (see Figure V-6 and equation (V-5))

15: RETURN (*Event*, α)

The labelled marker set is identical to that shown in Figure VI-1 (Chapter 6). The *x-axis* in the experiments (i.e. data acquisition equipment set-up) is parallel to the target line for all motion events[16]. Stance is computed as dynamic body position relative to the target line.

Computer-based Transformation of Angles to Features

The purpose of additional angle transformation is the mapping of machine learning features to produce 1) monotone angle function transformation and 2) space conversion for 3D viewing and representation as in mathematically positive oriented x-y space.

Motion data are internally recorded in the right-handed 3D coordinate system. For the human mind, the inverse order of quadrants in transverse plane (as x-z plane in stick figure representation, Figure VI-1, Chapter 6) results in viewing angles seen as mirrored angles (Figure V-5).

In addition, the feet angles from forehands (motion event in racquet sports) are not necessarily all limited to the $-\frac{\pi}{2} < x < \frac{\pi}{2}$ interval. The tangent function is defined as $\tan(x) = \frac{\sin(x)}{\cos(x)}$ over the domain $-\frac{\pi}{2} < x < \frac{\pi}{2}$.

[16] See Vertical Rotation algorithm in Appendix B, for diverse motion capture orientation setups.

As an example, for feet position calculations, where stance angles α lie within the II-quadrant, the resulting feet angle calculations may change to negative (Figure V-6 b) – which is counterintuitive to the human mind, expecting monotone positive angle increase.

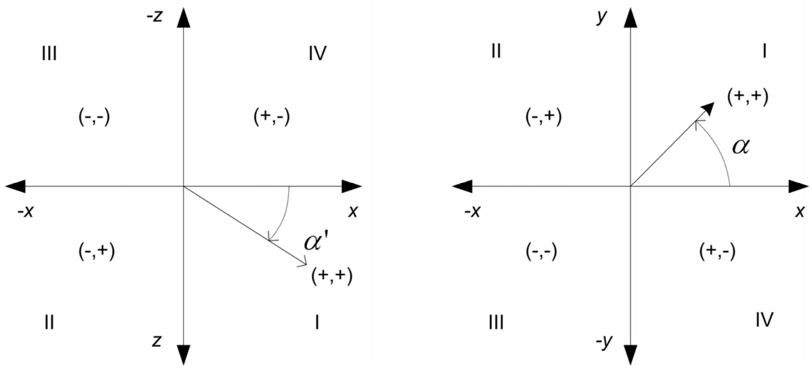


Figure V-5. Comparison of x-z plane of a 3D right handed coordinate system with commonly used x-y coordinate system (with quadrants I-IV ordered in mathematically positive direction).

For example, a monotone positive increase (Figure V-6 c) would be expected for feet angle α change for the interval between $[45 \le \alpha \le 135]$ degrees Figure V-6 a).

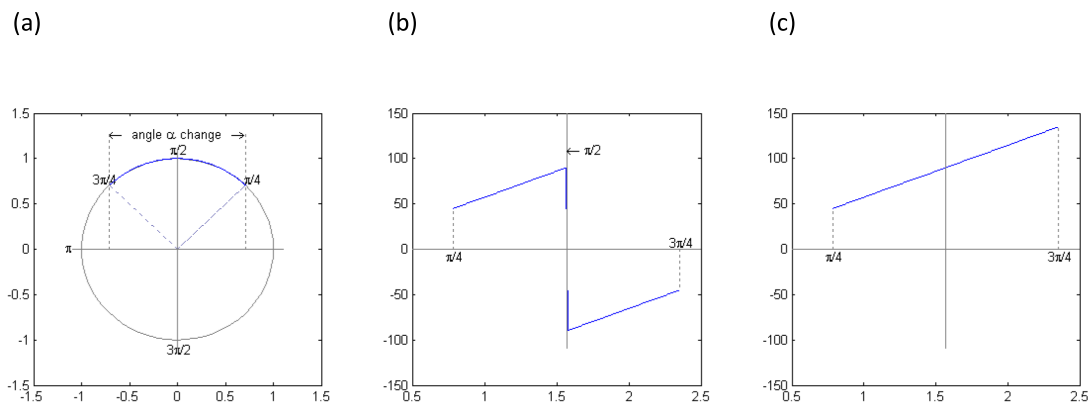


Figure V-6. *Arctan* function transformation for (a) a defined interval, from (b) non-monotone to (c) monotone function.

In addition, from a connectionist systems perspective it is also expected that monotone linear function approximations would be less computationally expensive (e.g. in number of committed neurons, clusters) than for cases of non-monotone or non-linear approximations. For negative angles in the IV-quadrant (e.g. closed-stance forehand), a design decision was taken in favour of preserving the negative angle sign over adding 360 degrees to a resulting angle (Figure V-7).

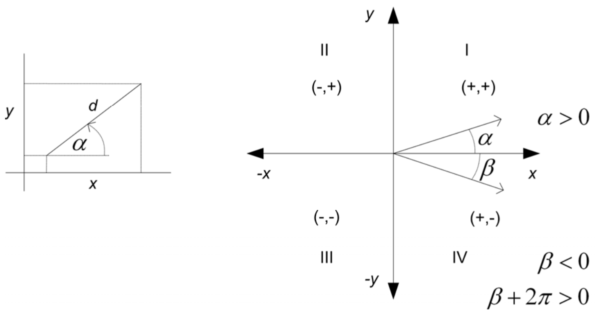


Figure V-7. Angle calculation between imaginary line d between feet and angle relative to target line x. Angles may be expressed as positive angle α within the interval of [0, 360] degrees or as positive and negative stance intervals.

The *transf()* function formula (V-5) for angle transformations in the algorithm for racquet sports is also configurable in taking into account coaches' preferences for angle expression related to the swing, kick or throw type action.

$$\alpha = \begin{cases} \left(\dfrac{\sum\limits_{i=newStartFrame}^{newEndFrame} \arctan\left(\dfrac{\overrightarrow{Zssm}[i] - \overrightarrow{Zpsm}[i]}{\overrightarrow{Xpsm}[i] - \overrightarrow{Xssm})[i]} \right)}{no\_of\_frames} \right), if\ \{BACKHAND\} \\ \left(\dfrac{\sum\limits_{i=newStartFrame}^{newEndFrame} \arctan\left(\dfrac{\overrightarrow{Zpsm}[i] - \overrightarrow{Zssm}[i]}{\overrightarrow{Xssm}[i] - \overrightarrow{Xpsm})[i]} \right)}{no\_of\_frames} \right), if\ \{FOREHAND\} \cap \{\overrightarrow{(Xssm}[i] - \overrightarrow{Xpsm})[i]) > 0\} \\ \left(\dfrac{\sum\limits_{i=newStartFrame}^{newEndFrame} \arctan\left(\dfrac{\overrightarrow{Zpsm}[i] - \overrightarrow{Zssm}[i]}{\overrightarrow{Xssm}[i] - \overrightarrow{Xpsm})[i]} \right)}{no\_of\_frames} + 2\pi \right), if\ \{FOREHAND\} \cap \{\overrightarrow{(Xssm}[i] - \overrightarrow{Xpsm})[i]) < 0\} \end{cases} \qquad \text{(V-5)}$$

Temporal and Spatial Filtering Uncertainties

Considering the filtering performed in steps #4 and #5 of the stance angle feature extraction algorithm (Table V-6), it is possible that experts' uncertainties/disagreements over narrow decision boundaries may arise from observed swing stances executed from non-steady (moving) positions. For example, for non-steady swings, the steps #4 and #5 computation may require additional rules to further reduce temporal ROI; or to produce an 'average' stance within the last temporal ROI interval.

The stance angle expressed in this example as a feature for machine learning is also comprehensible in terms of human reasoning (as a critical feature).

2.5 Feature Extraction Insights – Broadening the Context

The following critiques and views are expressed with the intention of bridging disciplines, broadening the context and expressed perspectives of the research reported here as well as highlighting the scope for further studies on FET:

- The 'feel'-equivalent ML computation (Figure V-4) and transformation of data associated with the human notion of 'feel' would involve numerically expressing 'feel' components such as: internal rotation and momentum 'feel' actions prior to impact/release, joint rigidity vs. elasticity 'feel'; and 'push through';
- The difference between the machine-based temporal and spatial feature extraction (introduced in Figure IV-17) and qualitative temporal phasing observation is that the generic multistage ROI computation for individual coaching rule feature extraction: (1) Is not bound by ROI observation focus of body segments, but it may include any interrelated subset of markers; (2) Temporal phasing (preparation, action, follow through) may be extended to more than three phases and temporal ROI observation may not be strictly bound within an individual phase; and (3) Machine pattern recognition from motion activity may require multistage temporal and spatial ROI filtering;
- Event detection (noted as S_j in Figure IV-17 and in event recognition Table V-3) are expected to employ CI approaches, computer vision mixed with traditional algorithmic-based computation and be optimised for either speed or accuracy. The proposed approach may also be combined into a hybrid approach with prior work including sound and impact vibration filtering and detection; and
- Stance (Table V-6) CR is an attributing factor to complex execution of balance and balance transfer throughout the characteristic motion event. Stance CR computation for each discipline may require modification of the generic algorithm (see Table V-6). Static balance as achieved equilibrium could be transferred to machine assessment similar to the task sheet model (Chapter 2). Dynamic balance at present is considered as a complex research area of processing, with equivalent results to a human mind abstracting *kinesthetic proprioception* with sensory inputs and internal and external forces during the movements.

3. User Interaction Aspects Linked to Application Front-end Prototype

The prototype is intended to demonstrate integrated concepts relevant to motion data analysis. Interactive tasks associated with the processing of motion data samples include expert assessment, training and validation of connectionist-based modules and flexible assessment criteria (via sub-space modelling, orchestration and machine knowledge extraction/insertion). The general capabilities delivered via algorithm integration operating on 3D motion data are illustrated using 3D tennis motion data and coaching rules – linked to the case study that follows in Chapter 6.

The user interface is designed to hide the complexity of background processing (using connectionist approaches) and to communicate assessment of motion data files based on human-comprehensible (coaching) rules and associated criteria.

The extracted machine features from 3D tennis motion data (from Chapter 6, case study) are utilised for CI-based assessment to mimic (coaching) rule-based assessment conducted by humans. For the purpose of automated assessment, the prototype supports both autonomous and manual (visual interactive) data selection for training/testing and validation of connectionist systems responsible for performance assessment.

Interactive selection of ML features as data samples for classification modules is enabled utilising 3D visualisation of the original motion data. Autonomous data selection for the purposes of training and validation supports initial modelling scenarios utilising small data sets that can be extended at a later stage. A user may also select validation methods (see Table III-2) such as: LOO, iB-fold (Bacic, 2008b), holdout, and the like.

The main intent of the user interface design can be considered in terms of the following goal statements:

1. Interactive prototype for data analysis and modelling of human motion. The GUI front-end enables end-users to accomplish common tasks without the need for coding or entering commands via a keyboard. Linked to the GUI front-end, MATLAB™ background processing utilises existing prototyping programs (FET, ECOS), whose intermediate processing data can be further examined, processed or visualised.

2. Leveraging expert insights. The GUI prototype enables 3D visualisation of motion event samples linked to extracted ML features, expert grouping (including *data labelling*) and assessment validation as classification comparisons between humans and a connectionist system. Those common tasks can be achieved directly via the GUI or directly in the MATLAB computation (COM) server, whose background process visibility (or accessibility) to an end-user is also controlled via the GUI. Using session control between the GUI and the COM server (Figure V-1), it is also possible for an end-user to include additional interim computational steps manipulating intermediate operation data.
3. Proof of concept testing that includes different coaching rules and ML feature extraction integrated via a high-level rapid prototyping programming language.
4. Extensible modular structure that can evolve. As they are independent of the GUI the assessment modules can be modified or replaced. In addition to evolving assessment modules (utilising ECOS classification) the entire assessment structure can be extended or reduced in terms of the number of CREMs orchestrated for a targeted assessment criterion.
5. High-level concepts that can be transferred to other human motion activities.

3.1 Augmented Coaching Application Context

Selected demonstrations of CR in this thesis are based on and reflect demonstrable principles of fundamental technique assessment. Interaction with individual samples is designed for off-line operation and modelling. With manual selection of new samples, an end-user may investigate how system knowledge evolves or displays a learner's progress in particular shot sequence assessment, hence simulating on-line operation mode without the need for motion event parsing[17] and predetermined normalisation min and max values (required for extracted features).

For an end-user, a pre-selected set or sequence of motion events also enables the investigation of system behaviour regarding: 1) learning progress or 2) tracing of incremental progressive skill acquisition as an indication of personal technique achievement.

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[17] Event parsing of tennis swings is demonstrated in Chapter 6, with tennis swing recognition and with temporal phasing FET

From the perspective of personalisation, a coach may select which rules would apply to a selected group or individual and adjust their importance (weights) for automated assessment. If a particular CREM is not implemented, a coach may help in creating a new CREM, to be added later to the prototype, by taking into account the context (previous chapter) and the framework (Figure IV-9). For user scenarios in which a coach may or may not be familiar with a particular CREM operation, a coach may compare in isolation his/her expert's assessment against CREM classification validation on the same data set.

3.2 Application Prototype and Specific Tasks Requirements

In the previous chapter the diversity of assessment criteria was described, covering aspects such as CS (Figure IV-5 and Figure IV-6), and learner and coaches' preferences. As a result the prototype is intended to be flexible and accommodating of such diversity, providing personally modifiable aspects at the front-end level and at the back-end allowing for CREM to be trained as personal, group/CS or global modules. Such requirements are also embedded in the flexible UI that enables interactive selection and supports the modular scalable architecture. For example, the MoHEM/CREM modules should be integrated as *add-ons* (following the plug-in concept) managed by the GUI front end.
Chapter 6 reports the practical examples of CREM modelling (Figure IV-10), supporting the underlying architecture (Figure V-2).

3.2.1 Research Framework and Visualisation Support

The research framework supporting back-end processing is primarily focused on incremental implementation of heuristics with the goal of ML motion assessment. Modelling activities associated with machine motion data processing e.g. MoHEM/CREM design, are not expected to be conducted in the front-end but rather using other specialist programming environments.

Visualisation Tools and Tasks

The visualisation toolkit supporting all stages of the research framework (Figure IV-10) incorporates 2D and 3D graphing (e.g. MATLAB plot function library) and a stand-alone animated interactive 3D stick-figure player. A subset of these visualisation tools is included and modified in the GUI prototype e.g. the 3D stick figure viewer is added to the GUI with the purpose of exchanging and depicting assessment results (Figure V-8) for the currently observed motion file, therefore operating in singleton operation mode. For qualitative assessment such as assigning labels ('good', 'bad') and similarity grouping, it is also possible to run simultaneous multiple instances of the stand-alone version of the 3D stick figure viewer. Simultaneous viewing of ten motion samples has been found to operate successfully without noticing 'freezing frames' (tested on single core CPU/2.2 GHz with 2 GB of RAM).

3.2.2 Synchronising Data Linking and Representation

3D motion data samples for end-user viewing and qualitative assessment are linked to their individually represented ML data samples. ML data samples contain features that are computationally derived (or extracted) from 3D data and the expert's data. The extracted features are required for the purpose of automated motion event assessment while additional discrete data values of the expert's prior assessment are required for the purpose of training and validation of a connectionist system. Each individual 3D data sample is a temporal portion of continuous motion data sequence that contains an individual event. A racquet sport event sample – for instance, a swing sample – includes initial foot movement, followed by preparation, backswing, swing and impact until the end of the follow through and recovery phase.

For the purpose of ML, data for off-line modelling are provided by a set of independent modules utilising CREM-specific feature extraction from selected motion data samples. For modelling, training and validation, feature data for ML are extracted a-priori and stored together with motion data. Feature filtering, based on temporal and spatial computation is demonstrated further in Chapter 6.

3.3 Front-End Client: Users, Tasks and Requirements

The interface (Figure V-8) for the prototype's front-end client is designed as a trade-off of complexity and cognitive load (such as number of visual interactive items that can be grouped visually into tasks associated with operational intention), specific to a user profile. In addition, a 3D player that can operate as a standalone program in multi-view mode is integrated into the client. Integration is exhibited as two-way communications (e.g. similar to a media play list, in which the playing activity is synchronised between the front-end client and a 3D viewer); the front-end can invoke 3D viewing in singleton mode for the current sample, and pass information such as a motion sample data; on user request the 3D viewer can replay a sequence, leaving the next motion event sample waitlisted in the virtual queue.

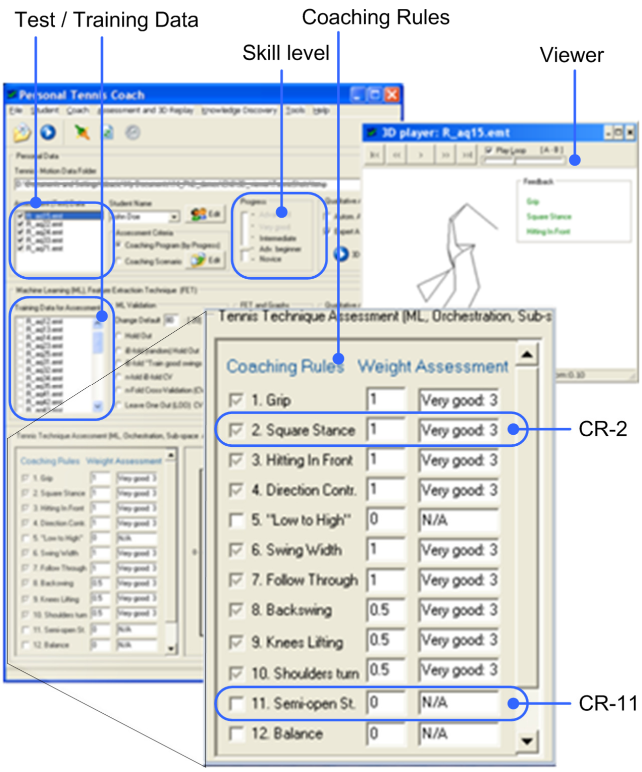

Figure V-8. Proposed interface as the GUI front-end (left-hand side) is supporting connectionist methods with integrated 3D viewer. The user interface shows visualisation of tennis motion data and CREM module integration from the case study (Chapter 6). Flexible stance CR assessment is shown as CR-2 and CR11.

For the educational purposes of augmented coaching, the prototype is intended to provide augmented 3D replay capability with flexible diagnostic assessment of a currently observed motion event.

3.3.1 User Profiles

The front-end (Figure V-8) is designed to suit four user profiles:

1. Learner, who can follow personalised progressive achievements, review prior movements, compare expert and machine assessments and select a skill level and follow a recommended coaching scenario (to address specific skills acquisition).

2. Coach, an expert who can store his/her criteria, CS, demonstration motion samples and trained CREM knowledge, and can advise learners regarding the most appropriate settings for the next coaching scenario and their analysis of the captured data.

3. Analyst with cross-discipline expertise in kinesiology, biomechanics and CI, who can create new methods, models and module implementations.

4. System designer, implementing and integrating new modules and overseeing overall connectionist/KE approaches for motion data processing in the back-end. The front-end application provides the interface and modular interconnectivity to another programming environment (MATLAB ™), responsible for back-end operation such as MoHEM/CREM processing tasks.

Specific functional aspects for users require information persistence between the use sessions of a prototype – warranting the use of a database[18].

3.3.2 Database Purpose and Utilisation by User Profiles

To support the functionality needs of the different users and to retain data between use sessions an intended database associated with the prototype should manage the following:

- Instant access to previously stored motion event samples;
- Predefined programs for skill level and weighted selection of CR;
- A repository for various CS e.g. drill-based coaching sessions with weighted selection of CR and demo event samples (e.g. if a coach prefers video over his/her demo or as instructional material for standardised progress/skill level/CS programme). Where needed, data samples may be grouped into categories and associated with start-up information and optimal virtual camera viewing details;
- Individual coaches' assessment criteria as machine knowledge;
- Learner's previous data samples and progress; and
- Prototype default start up and other operational settings.

[18] As a concept of storing and retrieving information. Database systems as a discipline is outside of the scope of this study.

For prototyping purposes, data are stored in ASCII format and event samples are stored as individual files.

3.4 Novel Visualisation Supporting Augmented Coaching, Modelling and Qualitative Analysis of Motion Data

In order to support augmented coaching, modelling and qualitative analysis (and also to demonstrate novel approaches developed in this thesis), a practical solution requires external synchronisation for visualisation and replay. This solution supports flexible and automated replay tasks linking selected ML data samples with their equivalent (or representative) motion data samples.

3.4.1 The Need for a Visualisation Tool as a Bridging Link

An observation and replay tool is a prerequisite in automated assessment inference modelling and expert labelling in diverse sport disciplines. A video or 3D stick figure player as a tool for observation (and replay) is needed for viewing and qualitative assessment from appropriate viewing angles, to enable rigorous analysis from the perspective of biomechanics and kinesiology discipline (Knudson & Morrison, 2002). In a 2D scenario, as part of a video acquisition protocol, the vantage points – placement of the camera – must be reported in research, while in a multi-camera 3D acquisition scenario, research would also report on acquisition volume and sampling resolution/frequency. 3D visual assessment supports a virtual camera view, implemented via 3D to 2D transformations from the original 3D data to enable 2D screen viewing.

The benefit of using an *external synchronisation for visualisation and replay* as a visualisation tool in *supervised learning* can be demonstrated, for example, in visual stance assessment. Such an approach is closer to human stance assessment than asking an expert for numeric angle values defining correct or incorrect stances. Determining stance angles subsequently can be based, for instance, on average values extracted from a neuro-fuzzy connectionist system as a set of rules, or it may also be analysed and computed directly from the available data. In addressing the issue of human decision boundaries, selected motion samples can be compared by replay, synchronised externally by other software or manually e.g. by setting the same virtual camera viewing parameters for multiple viewing.

In general, viewing motion events associated with transformed data could be achieved through an application prototype (front-end) or by integrating a viewer with other specialist programming environments. As added value to qualitative analysis, coaching via replay (augmented coaching) and *expert data labelling*, the novel concept of *external synchronisation for visualisation and replay* enables automation of replays for tasks such as: 'best' viewing angles for similar groups of 3D data, or synchronisation of comparative multi-view of the samples representing similar temporal events.

External Synchronisation for Visualisation and Replay in Modelling of Connectionist Systems

The novel concept of *external synchronisation for visualisation and replay* in motion data modelling and associated tasks of qualitative analysis is linked to three key points:

1) Parsed samples are extracted motion events from available motion data. Parsed or extracted samples are to be treated as data samples, subjected to analysis common to qualitative analysis and modelling for machine learning.

2) Viewing of motion data and selected motion data sample(s) is enabled in both machine problem space (common to above mentioned analysis) and in human cognitive space (as qualitative replay analysis). Chapters 6 and 7 illustrate the results and visualisation aspects of machine learning space and associated views (for human observation) where appropriate. The chosen method is an animated stick figure with replay functions and a mechanism of integrative communication with an external system (software environment invocation, initialisation parameter passing or maintained from previous viewing, and interactive viewing features).

3) Selecting or supplying a mechanism to match viewed sample(s) with machine feature set sample(s) for modelling and training/testing or validation activities. *External synchronisation for visualisation and replay* of motion data events and associated machine data samples can be achieved through user interaction or in an automated fashion by an external programme or environment (such as an operating system environment or rapid development environment associated with a programming or scripting language). This can be technically achieved by program invocation parameters and a communication protocol between a viewer and the invoking program. For example, a part of a program may need information if a replay of a current sample has finished before proceeding to

actions associated with the next samples. In a such scenario, the program would supply sample information (about to be viewed) and receive updated status information from a viewer during its runtime to synchronise other program activities. The viewer can maintain its state (e.g. camera angle between different observing samples) or invocation status as a singleton (allowing qualitative analysis of a sample at time) or in multiple viewing operations (for analysis requiring sample comparison).

External synchronisation for visualisation and replay also includes programming techniques to support: *command line input parameters* and *event messaging*.

Technical Requirements for a 3D Viewer

Technical approaches underpinning the animated 3D stick figure design draws on established practice in computer graphics and game development. In embracing the growing importance of the gaming and digital entertainment industries, visualisation may be additionally extended to artistic design and *rendering* of *avatars* compared to 3D wire frame stick figure animation. However, real time 3D stick figure animation is not as computationally expensive as in general 3D gaming animation. Furthermore, interaction, functionality and accurate replays are expected to be of higher priority for qualitative analysis (e.g. responsive accurate 3D movements, restricted z-axis rotation) than creating a game-like interaction experience.

3.4.2 Enabling Human Assessment via External Synchronisation for Three-dimensional Visualisation and Replay Capability

In the era of video replay/VCR supported qualitative analysis, additional VCR interactive features used for video coaching and analysis were: frame freeze (pause), JOG/SHUFFLE, frame advance, play and (added later) Play A-B as a repeated sequence. With 3D motion data, VCR usability extends to the concept of virtual camera view control, which includes transformations (move, zoom, rotate) and a transformation processing pipeline commonly used in computer graphics (Eberly, 2007; Parent, 2008).

Specific 3D player design priorities adopted here, based on their perceived importance related to this thesis, include:

- Portability: Single executable file, able to be run without installation (e.g. from a memory stick).

- Accurate and smooth virtual camera movement through static or real-time animated viewing operation. For visual testing and coding of FET that includes event, angles and other comparisons, the current status (e.g. frame number) and other reference data (e.g. coordinate origin) must be displayed.
- Multiple-viewing or singleton-restricted operation mode, without animation delays ('freezing frames').
- Functionality associated with interaction (such as capture of frame(s), storing replayed frames as individual files, reset view). For example, for qualitative analysis, an implementation decision of choosing to restrict virtual camera rotation of the vertical axis only matches the common natural observation tendency to keep the eye level horizontal. This restriction would not apply to augmented coaching scenarios such as: bob sledge or acrobatic flying.
- Communication and integration with hosting application or processing environment. The program can be invoked with pre-loaded motion data (externalised synchronisation feature) from other programs, via a command prompt or from MS Windows file explorer, MATLAB or other applications. Communication permits analysis and video coaching with a predefined data table containing the playing order of multiple motion files and commands for their segment viewing (e.g. paused/play, A-B looped). Virtual camera view parameters can be pre-set to allow multiple motion files to be compared e.g. at the same frame or characteristic event occurrence in multiple viewers. As an illustration, a single command can close all currently open viewers to allow the next viewing set of motion files. In another example, the hosting application (Appendix D) can obtain the status of the currently played motion file.

3D to 2D view

A stick figure topology of a 3D wire frame model is drawn in 2D screen view via *xyzTo_x()* and *xyzTo_y()* functions (Table V-7 and Table V-8) that may be already available via installed graphics libraries or via 3D graph tools. Independent of installed graphics libraries, this approach is based on the two functions (Table V-7 and Table V-8) engineered for CPU processing[19] of 3D to 2D points transformation.

Table V-7. Computing x pixel location on the screen 'canvas' from 3D motion data.

Function xyzTo_x(x,y,z)
1: $result \leftarrow mh + round(x \cdot \cos(CameraView.h) + z \cdot \sin(CameraView.h) \cdot CameraView.sz)$
2: RETURN $result$

Table V-8. Computing y pixel location on the screen canvas from 3D right-handed motion data.

Function xyzTo_y(x,y,z)
1: $result \leftarrow (mv + round((y \cdot \cos(CameraView.v) + (z \cdot \cos(CameraView.h) - x \cdot \sin(CameraView.h)) \cdot \sin(CameraView.v)) \cdot CameraView.sz))$
2: RETURN $result$

Where:

$mh = round(\frac{horizontalPixels}{2})$ … is the half of the screen 'canvas' length in pixels[20]

$mv = round(\frac{verticalPixels}{2})$ … is the half of the screen 'canvas' height in pixels

$CameraView.sz$ … is the virtual camera zoom
$CameraView.h$ … is the horizontal virtual camera angle
$CameraView.v$ … is the vertical virtual camera angle
round() … round to nearest Integer number.

Drawing a Stick Figure Topology

The animation effect can be achieved by redrawing a stick figure over the screen or form canvas (or in a 3D graph if available) at regular time intervals that are matched with the sampling rate of the acquired 3D motion data.

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[19] Acknowledgement: General explanations on wire-frame/mesh computer graphics and a 3D to 2D points transformation demonstration (by Josh Code, greijos@hotmail.com) inspired CPU based 'stick figure' computational approach (http://www.programmersheaven.com/d/click.aspx?ID=F23102, accessed in Dec 2009).

[20] The algorithm performance can be improved by programming frequently computed formulae in Assembler. E.g. the equivalent formula mh = shr(horizontalPixel) requires a single CPU instruction cycle, which can replace operations (integer division by two and rounding) by right-shifting binary number.

User mouse gestures and keystroke combinations are interpreted as designated commands for changing viewing parameters between every frame computation (achieved in real-time). This approach provides the user with the experience of smooth and accurate interactive motion control of the virtual camera view during playback.

Table V-9. Drawing a stick figure on a 2D 'canvas' from a single 3D right-handed motion data sample.

drawStickFigure(3D points sample, wire frame topology)

```
1: lines ← combineTostructure(wire frame topology , 3D motion data)
2: FOR i ← count(lines) DOWNTO 1 DO

// the first point of the line
3:      moveTo(xyzTo_x(lines[i].p1.x, lines[i].p1.y, lines[i].p1.z),
               xyzTo_y(lines[i].p1.x, lines[i].p1.y, lines[i].p1.z))

// draw the line from the first point to the last point of the line
4:      lineTo(xyzTo_x(lines[i].p2.x, lines[i].p2.y, lines[i].p2.z),
              xyzTo_y(lines[i].p2.x, lines[i].p2.y, lines[i].p2.z))
5: END FOR
```

4. Chapter Conclusion

The framework and architecture described in this and the previous chapter have been developed to be universal, adaptive, to work with initially available sparse data or large-scale data sets; and yet be sufficiently simple to cover the fundamentals of general human motion modelling in a variety of sport and rehabilitation domains.

Given the competitive and evolving nature of sports disciplines, the introduced framework and extensible and evolving architecture address the challenges of: (1) Extensible and evolving incremental development of motion assessment capabilities; (2) Flexible and subjective assessment relying on evolving machine learning; and (3) Human-intelligible assessment feedback.

Human-intelligible feedback is addressed via replay and itemised diagnostic-elements (developed in Chapter 6) as analysis of observed motion events. Each diagnostic-element item represents MoHEM/CREM operation on motion data to provide output as descriptive assessment categories i.e. as output labels. The evolving architecture integrating ECOS linked to a user interface with replay capability provides a viable solution for ACS.

The *front-end* user interface is viewed as a generic concept – unifying ML/connectionist approaches with expert's assessment and various user-centred tasks associated with sporting activities (Figure V-9). The user interface with motion data visualisation are surrounding, wider objectives of this thesis and at the same time they represent enabling technology supporting the design framework.

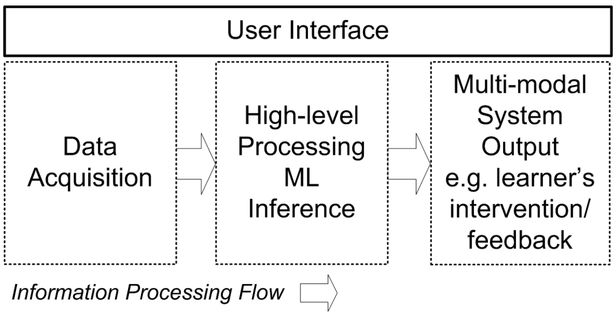


Figure V-9. Augmented coaching system – logical tasks separation, modified from (Bacic, 2008a).

This interaction model (Figure V-8) provides a 'bridge' between the 'High-level Processing ML Inference' and 'Multi-modal System Output' stages (Figure V-9) intended for future work. The general role of the UI and visualisation is to: (1) Present replay capabilities with high-level assessment to an end-user, while hiding the complexity associated with 3D motion data and connectionist modelling; (2) Facilitate expert assessment by providing accurate view and specific replay usability functions; and (3) Enable learning as visual motor rehearsals and replays of motion data samples (e.g. as extracted tennis swing data in the first case study).

Software component integration with motion data visualisation for this thesis is facilitated by novel *external synchronisation for visualisation and replay* functionality. A multi-layered modular architecture (Figure V-1) is developed to demonstrate general principles independently of the motion data acquisition and back-end processing tasks. For such generic reasons, the UI, distributed processing and visualisation focus is covered in this chapter separately from the case studies (Chapter 6 and 7). Automating coaching analysis based on flexible and subjective criteria utilising generic stance feature extraction is demonstrated and tested in the next chapter.

Chapter 6

VI. A CASE STUDY OF MODELLING HUMAN TENNIS ACTIVITY

Qualitative assessment of human motion is a systematic and yet subjective activity open to interpretation of a key question: what is the goal of each assessment? This chapter describes the conduct of a series of novel experiments (started in 2003 and continued up until the previous year), that have utilised the approach described in previous chapters to automate aspects of qualitative assessment by combining connectionist and other approaches found in the discipline of computational intelligence.

This group of experiments on tennis data is considered the main case study in this thesis, demonstrating the application of connectionist approaches in automation of qualitative assessment in augmented coaching.

The chapter structure and grouping of the embedded case studies are organised to address evolving practical questions reflecting on the outcomes achieved and to build foundations of experimental evidence to address the main research questions in this thesis.

1. Introduction

This chapter provides experimental evidence through which the higher-level questions set out in chapters one and two can be answered. As a starting point specific to tennis, the intent of this case study is to answer the question:

Can a machine accurately detect good and bad tennis shots?

The fundamental assertion central to this thesis is that motion assessment can be automated by combining connectionist and general CI methods with qualitative analysis of human motion.

In addition to autonomous swing detection, this chapter reports on evidence supporting previously introduced derived observational models and concepts and the framework enabling prototype construction.

1.1 Background

Doubles aside, tennis is considered to be an individual and open-skill sport (Figure IV-6). As such it brings particular challenges to the building of a useful and effective prototype as well as to the use of that prototype in the assessment of tennis shots. This is due in large part to the real-world variations in a large number of individual factors, such as: grip, hitting stance, technique, individual playing style, anthropometrics/biometrics, agility, flexibility, mental approach to the game, age, gender, out-of-comfort-zone/under-pressure technique adaptation, and others.

The connectionist approaches applied here are executed via background processing (see: Back-end MATLAB™ COM server, Figure V-1). The selected tennis heuristics and CR considered in the experiments are aligned with the fundamental concepts and principles of tennis, such as those included in the "traditional method"[21] originated by Van Der Meer. Some of the more abstract or strategic/complex principles requiring more available data, applied by experts when scouting top tennis talents or selecting sponsorship candidates (Appino, 2010), are considered to be included based on the foundation of these experiments.

[21] A method for coaching tennis adopted and modernised world-wide.

1.2 Research Context and Experimental Design

The cyclic nature of the research and the development/use of the prototyping framework in this case study, as shown graphically in Figure IV-10, can be summarised as follows:

1. Select sport domain (tennis, in this case)
   - Identify key factors – to evaluate human motion
   - Identify and develop hypothesis
2. Design experiment
3. Collect data
4. Generate models
5. Evaluate results
6. Revise steps 2-5
7. Integrate models – to explain high-level and generic system properties
8. Identify key components of integrated models for control and further directions
9. Revise and modify models – to be re-applied to a new sport domain
10. Repeat the above steps for new domain (golf in this case, as addressed in Chapter 7).

2. Data Collection and Laboratory Setup

Motion data for this case study has been obtained in a laboratory from a capture system (SMART-e 900, developed originally by eMotion[22]) using 9 cameras (at 50 fps with resolution of < 0.3 mm on a volume or 3x2x2 m). The input data was exported into ASCII text format showing recorded *(x, y, z)* positions of a set of infrared retro-reflective markers attached to an arbitrary selection of characteristic 'bony' anatomical landmarks on a tennis player's body and a racquet. Markers' coordinates, as multi-time series data, have been recorded using a right-handed 3D *(x, y, z)* coordinate system (Figure VI-1).

Motion data (47 captured tennis swings) were obtained from a single person – a tennis expert (the author of the thesis) acting as a player with novice to intermediate skill level when performing typically 'good' and 'bad' swings (i.e. mimicking characteristic swing patterns and *common errors*). Prior to this data acquisition, typically good and *common error* swings were performed and recorded interchangeably by two different tennis experts over a number of

[22] Acquired by BTS Milan: www.bts.com

days, with incremental improvements, until agreement was reached on the laboratory protocol, occurrence and execution of commonly observed mistakes.

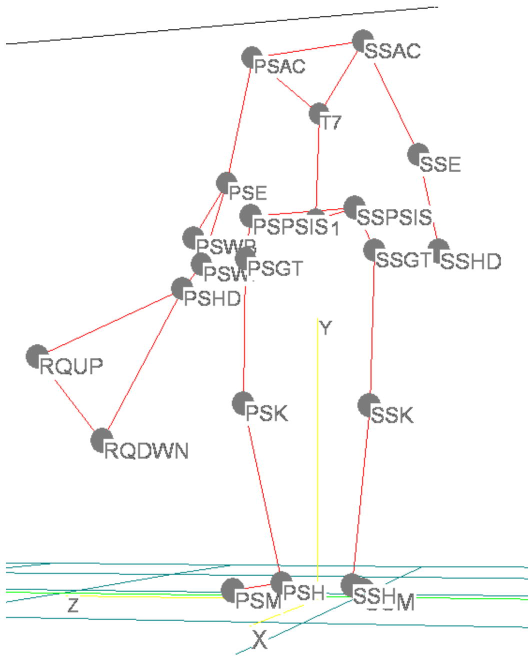


Figure VI-1. Tennis player's stick figure model represented with labelled markers in right-handed coordinate system. The x-axis orientation is parallel to the intended target line.

The final data acquisition occurred in one session, without the need for marker reattachment or camera recalibration. A second qualified tennis coach, (resident clinic's professional) was responsible for the data capture and laboratory setup (see Acknowledgement).

Note that due to restrictions on laboratory space, the acquired data did not include the ball or player's position relative to a court. It is asserted here that ball information is not required for qualitative assessment of stylistic execution of tennis swings, whether for human- or machine-based connectionist assessment approaches evaluated in this study.

For the purpose of maximising inter-rater reliability, the acquired data were manually and independently labelled by the two tennis experts into two distinct groups of good and bad tennis swings. The two experts reached 100% agreement in their classification of the swings into the groups based on their assessments of the captured motion data. Further validation of the views expressed regarding common errors and swing executions was achieved by the two independent, elite coaches in New Zealand, who inspected only 3D motion data via the animated 3D stick figure viewer (see Appendix E).

3. Experimental Evidence

The reported experiments and evidence (from multiple investigative development case studies) are logically grouped into three categories, distinguished by consequent milestone advancements in implementation, architecture, framework and overall contribution to the thesis (Table VI-1).

Table VI-1. Experiments summary including multiple investigative development case studies grouped into three categories.

Experiment	Main questions	Milestone advancements – summary
1. Global assessment model.	Can a machine accurately detect good and bad tennis forehand swings?	This experiment suggests the answers to the following: How to demonstrate a machine-equivalent qualitative evaluation model relying on small-scale data? Is it possible to demonstrate machine implementation similar to Gestalt principles/'top-down' observation of swing assessment that may indicate that e.g. "something may not be right in a big picture"?
2. Tennis swings extraction and recognition.	Can motion events be automatically extracted from motion data?	This experiment demonstrates automated recognition of tennis swings from 3D motion data as multi-time series temporal segmentation of the region of interest. Assessment automation can be achieved in near-real time by combining experiments 1 and 2.
3. Adaptive assessments and evolving principles.	Can a machine identify errors in stylistic movement execution according to human-intelligible rules? Can assessment criteria based on error identification be subjective, flexible and adaptable?	This set of experiments demonstrates the applicability of a range of topics/theories/concepts with high-level transferable properties to other sports and related disciplines. Machine evolving principles build upon and extend the structured and formal observational models, spatial and temporal segmentation by also including: bottom-up modular assessment, diagnostic outputs, incremental architecture and rule based performance assessment, performance criteria, evolving rules extraction, sub-space modelling, and weighted and connectionist orchestrations.

The obtained results, prototypes, architectures, modelling findings and related decisions are linked to prior chapters. With respect to Figure III-1 and the connectionist approaches discussed in Chapter 2, the tennis experiments considered in this chapter have the property of being 'theory-rich' and the heuristics reflect relatively large problem space dimensionality and the requirements of small data set modelling. No attempts were made to synthetically create missing marker positions from some of the captured data samples or to create artificial data to augment the existing data set with additional synthetic samples.

3.1 Experiment 1: Global Assessment Model

In terms of skill acquisition, Handford, Davids, Bennett, & Button (1997) summarised previous studies and concluded that a tennis forehand stroke suffers a 'curse of dimensionality'. Learning such a stroke requires a player to co-ordinate 800 independent muscles acting around numerous (100) joints and must account for physiological considerations and individual variability in anatomical and mechanical properties. In the absence of a single 'best' biomechanical model of a forehand stroke, the large number of possible stylistic and strategic executions (Crespo & Higueras, 2001; Bahamonde, 2008; McLennan, 2009) and stances (Knudson, 2008a) had to be considered and investigated. Taking into account that connectionist systems in general may operate well in high-dimensional problem spaces, Experiment 1 investigates the following: (1) If a connectionist system can be utilised for forehand stroke assessment; and (2) If so, can a connectionist system classify forehand strokes based on a relatively small data set?

The starting hypothesis was to create and evaluate a machine-based capability equivalent to an assessment of a player's 'feel' around the impact or action zone. If motion capture systems are capable of providing sufficiently accurate data measuring movement actions over a short period of time (60-120 ms) around an estimated impact or action zone, the resulting hypothesis asserts that it is possible to accurately observe hitting, throwing, and rebound surface motion vectors, and evaluate the performance of motion event(s) associated with the impact or action (Bacic, 2003a).

3.1.1 Data Analysis for the Global Assessment Model

For the purpose of the experiment, out of the 47 captured tennis swings, data analysis revealed that 14 forehand swings contained the complete markers' track information needed for the machine feature extraction. The motion swing data representing a 'time event' around the impact zone consisted of up to 13 frames (for the slowest forehand from the acquired data). In Figure VI-2 it is possible to visualise clusters of good and bad forehand swings in the 2D representation of the 3D view.

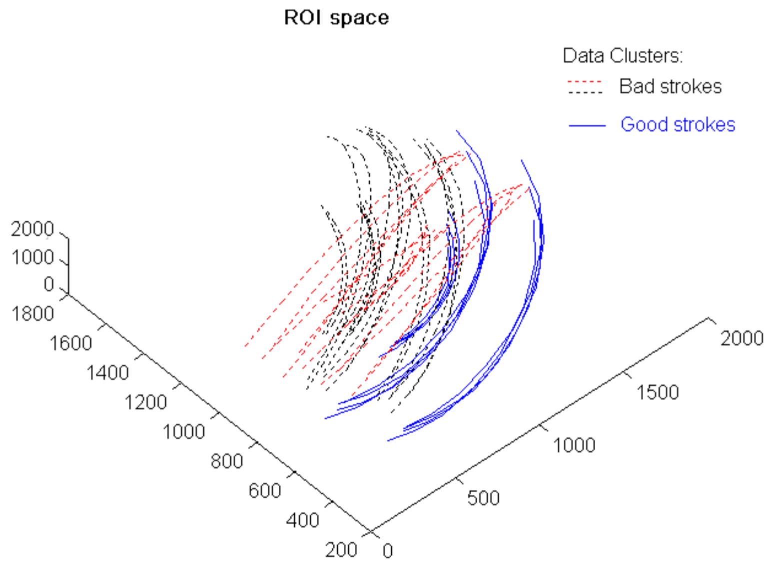


Figure VI-2. Clustering visualisation of forehand swings in three dimensional view.

3.1.2 Feature Extraction Technique Insights

For the purpose of testing of the hypothesis, at least three points should be used to assess a stroke. The three selected referencing marker tracks (Figure VI-1) required for machine feature extraction that represents a stroke motion are labelled as:

1. RQUP ... racket's head upper marker
2. RQDWN ... racket's head lower marker
3. PSHD ... player's hand marker.

The markers' non-linear motions were presented as a multi-time series of marker positions and as curvature shapes and were transformed using polynomial interpolation (VI-1):

$$f(x) = p_n x^n + p_{n-1} x^{n-1} + .. + p_1 x + p_0 \qquad \text{(VI-1)}$$

Where:
n … the polynomial order and
p … the coefficients.

Due to the momentum of the racquet (approximate weight 300 grams) and hand mass through the relatively narrow time interval around the impact zone, the selected marker tracks (RQUP, RQDWN, PSHD) as curves in *sagittal* and *transverse* motion planes were transformed as a second polynomial order with three parameters i.e. polynomial coefficients: p_0, p_1 and p_2 . Figure VI-3 shows the comparison between actual and interpolated data.

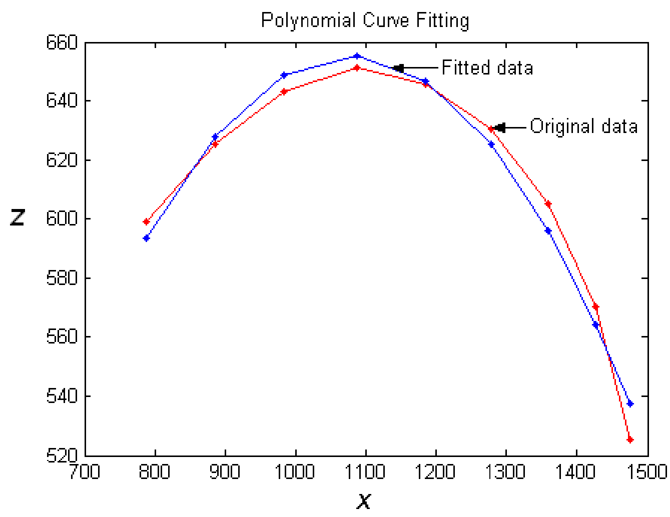


Figure VI-3. Curve fitting segment of a marker's trajectory within a time interval around the impact zone.

3.1.3 Classifier Modelling and Assessment Results

Supervised training and classification evaluation of the first experimental classifier prototype tested on this small data set was undertaken using the leave one out (LOO) cross-validation procedure.

Table VI-2. Leave-one-out cross-validation for forehand data utilizing an RBF classifier with 2, 3 and 4 hidden neurons.

Classification parameters and results		
	Number of cross-validations	20
	Number of input vectors	14
	Number of input features	18
	Number of output classes	2
	2 hidden neurons	66.4 [%]
Average classification accuracy	3 hidden neurons	99.9 [%]
	4 hidden neurons	99.9 [%]

Note: Classifier modelling steps taken to ensure that over-fitting was avoided include:
a sub-optimal model utilizing 2 hidden neurons and a possible over-fitted model with 4 hidden neurons that were tested and included in the results.

In addition, because of the random nature of the selected radial basis function (RBF) classifier training, the LOO cross-validation was repeated multiple times (20) as part of the validation process (see Table VI-2). The input feature set was normalised between [-0.8…0.8], before using the RBF classifier. The RBF code – written in MATLAB™ – is included in the NETLAB Toolbox (ver. 3.3)[23]. The NETLAB Toolbox is an open source product (available from: www.ncrg.aston.ac.uk/netlab/index.php, accessed 3 Apr. 2009) and it is also referred to in Nabney (2004) as the book's accompanying code.

Average classification accuracy ε is computed as the number of correctly classified samples divided by the number of all input samples (VI-2):

$$\varepsilon = \frac{1}{m}\sum_{i=1}^{m}\frac{N_{correct}}{n}\cdot 100[\%] \qquad \text{(VI-2)}$$

Where:

ε	… average classification accuracy as a percentage
$N_{correct}$	… number of correctly classified samples
n	… number of input samples
m	… number of cross-validations.

3.1.4 Experiment 1 Insights

The RBF architecture achieved an average classification accuracy of 99.9% on a relatively small data set. The machine learning problem space was in this case expressed as a high-dimensional mathematical space, with values altogether incomprehensible to the human mind. Even with machine features that are not necessarily identical to human-comprehensible biomechanics critical features (see Chapter 2), for the same observed/captured movement, the connectionist systems are still able to exhibit classification function properties needed to separate good and bad tennis swings. Gestalt grouping and proximity cognitive principles are demonstrated in this application of connectionist systems for human movement in sport and related areas.

A visual inspection of motion data did not reveal the need for a low-pass filter (i.e. to remove presence of high frequency noise). In observing polynomial curve fitting it is possible to conclude the following:

- Curve fitting may also act as a low band pass filter. The generalisation property of interpolation of known movement curves/shapes could be demonstrated by removing undesired high-frequency filtering (e.g. originating from sampling/digitisation noise);

[23] Acknowledgements for the RBF NETLAB code integration into: (1) this experiment – Dr. Zeke Chan and (2) the NeuCom [Ver. 0.920 Student ed.] software – Dr. Peter Hwang.

- Minimal differences were observed between the original and fitted (approximated) data (Figure VI-3) and classification results (Table VI-2) indicated that the fitted data should not influence the discriminant properties of features within the machine problem space and consequent classification accuracy;
- A concept of a transformation algorithm involving curve fitting could also be used for future higher accuracy capture systems, operating above 50 samples per second.
- The curve fitting method provides data compression; and
- Fitted curves or shapes contained in the problem space i.e. without a redundant noise component, could potentially provide better generalisation vs. overfitting in this classification problem area.

A shortcoming of this embedded case study is similar to that associated with a human holistic assessment; that is, while the machine-based approach was able to identify error in basic tennis swings, it could not articulate the rules that governed that decision. A second shortcoming is that the system was not able to evolve its operation utilising additional data in an incremental, life-long learning fashion.

3.2 Experiment 2: Tennis Swing Extraction and Recognition

A key goal of this experiment was to achieve a high-degree of automation of near real-time tennis swing extraction and recognition. Figure VI-4 depicts the integration of experiments 1 and 2.

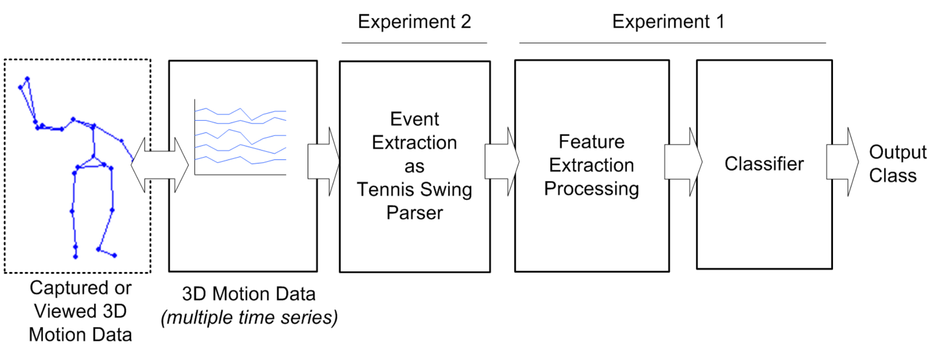


Figure VI-4. Integration of experiments 1 and 2 for automation purposes. Captured data are represented as multi-time series and viewed as 3D animated stick figure. The single head arrows represent the data flow between processing stages. Adapted from Bacic (2004).

When compared to the purpose of experiment 1, the added value of an incremental integrative design is in achieving a higher degree of assessment automation from motion data with testing and validation of the design milestones.

The focus in this experiment is the design and development of the processing stage labelled 'Event Extraction as Tennis Swing Parser' (Figure VI-4), whose operation was to be compared to a human expert who manually extracted the tennis swings, with their impact zone region of interest (ROI), as used in experiment 1.

3.2.1 Data Analysis for Tennis Swing Extraction and Recognition

Compared to the 14 forehands used in experiment 1, for the marker set to be used in the event extraction algorithm, data analysis revealed 5 additional data samples (meaning there were 19 forehands in total out of U=47 samples) suitable for event extraction algorithm validation.

The experimental input motion data are summarised as follows:

- Multidimensional topological representation of n-markers as a 3D stick figure (Figure VI-1) representing a human holding a racquet. Within each frame M, a marker m_i was defined as a point in 3D coordinate space (VI-3):

  $$m_i = (x_i, y_i, z_i)$$

  $$m_i \in M, \quad i = 1,..., n \tag{VI-3}$$

  $$M = (m_1, m_2,..., m_n)\,.$$

  Where M is a set of n markers.

- A tennis stroke S_j was a subset of a motion data set – a ($3 \cdot M$) time-series, containing random time delay between successive strokes. Each stroke S_j was a set of consecutive frames $M(t,\ldots,t+k)$ of individual duration k (VI-4).

  $$S_j \subseteq U$$

  $$m_i(t) = (x_i(t), y_i(t), z_i(t)) \tag{VI-4}$$

  $$S_j = \{M(t) \mid t_0 \le t \le t_{k-1}\}\,.$$

A motion sequence was described in this experiment as a 3D time series of rigid body positions over an arbitrary time period. Motion sequences constituting tennis strokes could also be defined as typical sets of *finite state automata*. Some motion sequences contained typical postures – spatial features, as a set of rigid body characteristic position patterns (e.g. hitting the ball phases).

After observing 3D animated stick figure samples and comparing the corresponding x and z axes' time series (Figure VI-5 and Figure VI-6) it was possible to recognise visually characteristic 2D patterns related to tennis strokes. Furthermore, the y axis' time series indicated the player's intention relating to impact energy transfer to ball rotation (e.g. slice or top-spin).

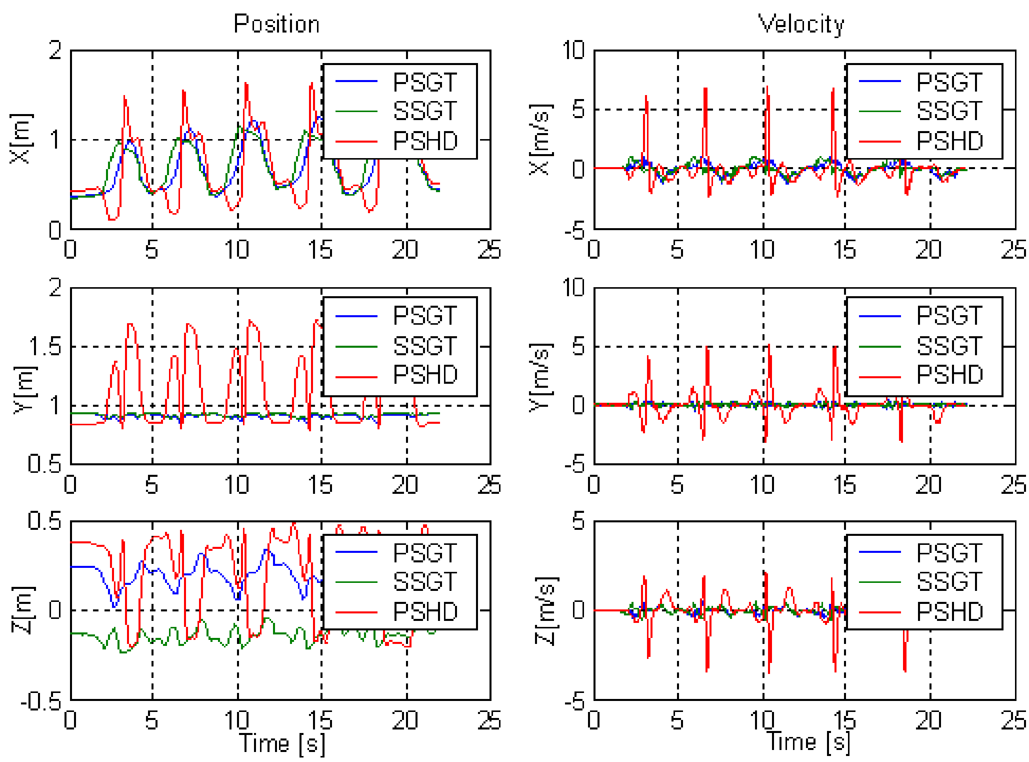


Figure VI-5. Selected markers' displacement and velocity time series for hips and hand swing motion patterns.

The heuristic rule for detecting the presence of a particular stroke type (e.g. backhand or forehand) relies on two mutually dependent parameters:

- Relative stroke magnitude (i.e. local stroke maximum within each sliding window W_i) – a descriptor: (1) insensitive to a player's absolute displacement (i.e. position), and (2) indicating the possible presence of a stroke within the current window neighbourhood as in Figure VI-6.
- Swing velocity relative to hitting orientation.

If both conditions of Phase I (Table V-4) were met for a given sliding window W_i then the Phase II computation (Table V-5) was invoked.

Figure VI-6 shows the results of the Phase I (Table V-4) computation, which recognised the presence of characteristic patterns of the five swings in a row. The five sliding windows' starting times, indicating the presence of characteristic swing patterns, are marked with vertical dashed lines.

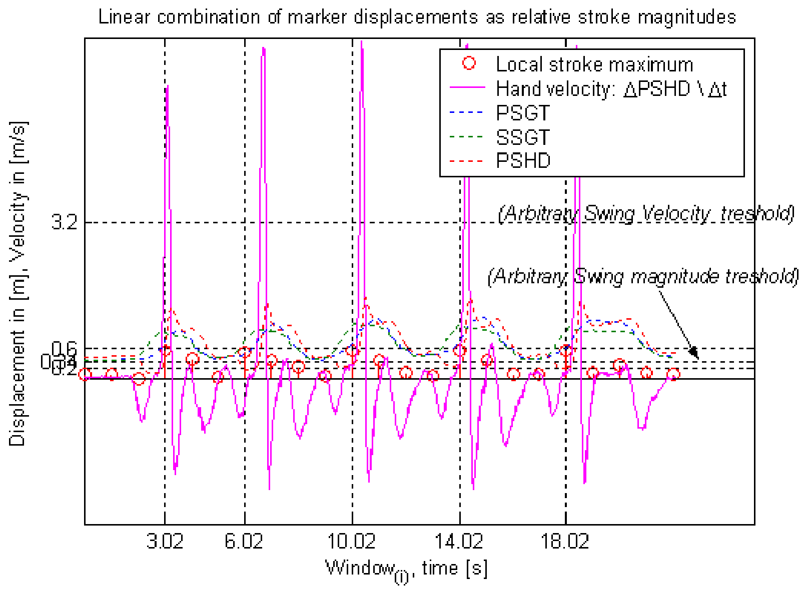


Figure VI-6. Stroke magnitude and velocity. For comparison the SSGT, PSGT and PSHD markers are superimposed with the computed swing velocity.

Although it is possible in real life tennis play for volley swings to be exchanged with ground strokes (forehands and backhands) at a rate faster than one per second, the chosen interval for the sliding window $W_i = 1$ [s] was sufficient to illustrate the recognition concept on the test data.

3.2.2 Feature Extraction Technique

The algorithm (Phase I: Table V-4 and Phase II: Table V-5, Chapter 5) for the ROI computation required as input only three (slower moving) markers motion data that were attached at approximately half of the player's height:

1. PSGT ... playing hand side great Trochanter
2. SSGT ... opposite side great Trochanter
3. PSHD ... player's hand marker.

The assumptions underlying this swing recognition experiment can be rationalised in terms of the different qualitative observational perspectives of a (tennis) expert versus a tennis enthusiast watching tennis. In the expert's view there are more and less important body parts that direct mental focus for a given time event during play. Translated into, and implemented by, a machine the *heuristic* that influenced the algorithm was related to the hip region (as early indications) and maximum hand acceleration (as the follow up indication) of characteristic curves relative to the target line before the impact.

Feature Extraction Technique and Generic Temporal and Spatial Computational Model

The two-stage computation of tennis swing detection was based on the generic temporal and spatial multistage computation for dynamic and static ROI (Table V-2 and Figure IV-17).

The first computation stage (Phase I) could invoke the second stage (Phase II) and pass the necessary parameters. The second stage concept was intended to access 'buffered' data without interfering with the continuous operation of the first stage computation. The first stage computation was responsible for evaluating the presence of a tennis stroke S_j, providing its ROI interval (start-frame, end-frame) from the available multidimensional time series contained a tennis swing.

When invoking the Phase II computational process (Table V-5), the sliding window data interval W_i was extended to include the prior and post window neighbours $W_i \leftarrow (W_{i-1}, W_i, W_{i+1})$. Ultimately, three markers (*SSGT*, *PSGT* and *PSHD*) time series were presented as markers' traces in the 2D transverse plane (x,z) in Figure VI-7. To visualise the motion pattern dynamics, an additional 'virtual' marker – 'Body centre' was computed for visual evaluation of the centre of the pelvis (or human body) in a transverse plane.

Since the markers' positions were obtained through the acquisition system with equidistant sampling time, each marker's velocity was calculated as the first order derivative of relative position displacement over time (VI-5), while acceleration is the second order derivative. Figure VI-6 shows the markers' calculated displacement and velocity. Further notions are detailed in Appendix B.

$$
\begin{aligned}
&\text{Position} = (x, y, z) \\
&\text{Velocity} = (\dot{x}, \dot{y}, \dot{z}).
\end{aligned}
\qquad \text{(VI-5)}
$$

Note:

The notation $\dot{x}$ represents the first derivative of *x* with respect to time as:

$$\dot{x} = \frac{dx}{dt} \text{ or } \dot{x} = \frac{\Delta x}{\Delta t},$$

where $\dot{x}$ is a difference between two points $\Delta x = (x_{i+1} - x_i)$ measured i.e. computed in time interval $\Delta t = (t_{i+1} - t_i)$.

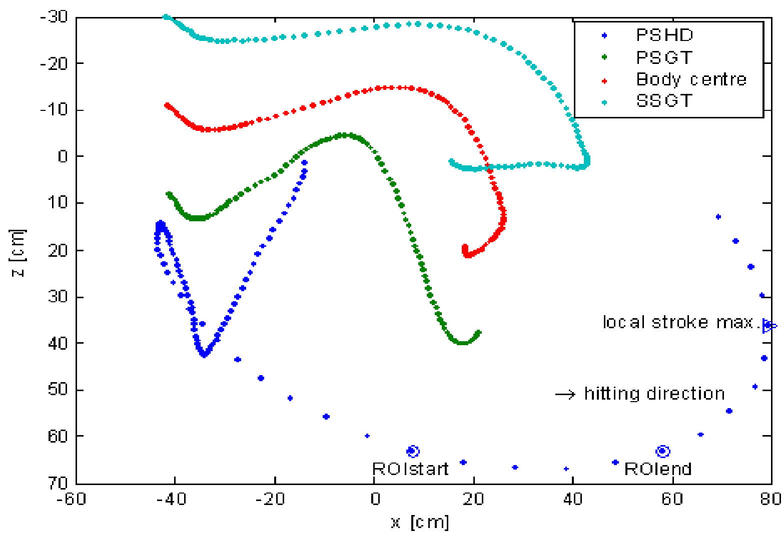


Figure VI-7. 2D transverse plane motion data view. The results of the Phase II variation computation are labelled as *ROIstart* and *ROIend*.

Algorithm Instantiation and the Experimental Context

In order to provide data for experiment 1, the generic two-stage algorithm was extended to the third computational stage – temporal filtering – to provide the impact-zone ROI_j (VI-6) extraction of the presence of a tennis stroke S_j from the available data set.

$$ROI_j \subset S_j \;;\; ROI_j \in [ROIstart_j, ROIend_j] \tag{VI-6}$$

In this experiment a variation of the Phase II algorithm (Table V-5) was designed to provide direct computation of impact-zone ROI_j, instead of producing a data sample interval S_j.

The second Phase II algorithm variation also included automated tennis stroke recognition (Table V-3) into forehand and backhand for the purposes of extracting forehand strokes.

> Note:
> The program for extraction of ASCII text formatted motion data utilising (start-frame, end-frame) parameters is shared as open source in Appendix C and is free for users to modify as needed. The intended purpose of this generic extraction program is: (1) to operate from *command line* environments (MS Windows based) and (2) to extract motion samples needed for machine modelling relying on an off-line motion sample database (Figure V-2) and (3) to provide parameters for novel *external synchronisation for visualisation and replay* capability.

3.2.3 Swing Extraction Results

The subjective results obtained from an expert (the author of the thesis) have been compared to those acquired from the prototype system (Table VI-3). The expert used 3D stick figure visualisation software (described in Chapter 5) to annotate time periods of selected ROI intervals for a series of tennis strokes U (p=19 forehands), with the complete markers' track information needed for the algorithm (Table V-4 and Table V-5) operation.

Table VI-3. Result comparison between the expert and prototype automated solution.

Expert evaluation				**Proposed solution comparison**			
File #	ROI Start frame	ROI End frame	Duration [frames]	Δ Start frame	Δ End frame	Duration [frames]	Δ Duration
1	157	162	6	0	0	6	0
1	333	338	6	1	0	5	1
1	519	523	5	0	1	6	-1
1	714	718	5	1	1	5	0
1	921	926	6	1	0	5	1
2	207	215	9	2	-1	6	3
2	372	381	10	3	-1	6	4
2	551	558	8	2	1	7	1
2	737	744	8	1	-1	6	2
3	340	348	9	1	-1	7	2
3	521	529	9	0	1	10	-1
3	695	701	7	0	-1	6	1
3	866	873	8	0	0	8	0
4	151	160	10	1	-1	8	2
4	326	338	13	1	0	12	1
4	506	516	11	1	-1	9	2
4	880	890	11	0	-1	10	1
4	1058	1068	11	0	0	11	0
5	864	868	5	0	1	6	-1

The labelled parameters in Table VI-3 are:

File # … motion data stream number
Δ … Delta = Expert_Value – Machine_Value.

The computed $ROIend_j$ frame number was further reduced (VI-7) from the local stroke maximum ($L\max_j$) (as also depicted in Figure VI-7). The extraction of the $ROIend_j$ parameter was subject to human heuristics and possibly inexact interpretation of the end frame of the ROI_j interval during the qualitative assessment of 3D motion data. This problem was addressed in the extraction algorithm through the inclusion of a parameter φ or angle Phi (φ) to keep the automatically extracted 'impact zone' interval as similar as possible to the manually extracted ROI intervals used as input data for experiment 1.

$$ROIend_j = f(L\max_j, \varphi) \quad \text{(VI-7)}$$

The best experimental results were achieved when φ = 0.25 (shown in the Table VI-4).

Table VI-4. Result summary.

Results summary					
Number of tennis swings in total	19				
φ	0.25				
	Duration	Δ Start frame	Δ End frame	Duration [frames]	Δ Duration
Average	8.263	0.789	-0.16	7.316	0.947
Max	13	3	1	12	4
Min	5	0	-1	5	-1
Median	8	1	0	6	1
Range	8	3	2	7	5

Note that although there was no impact recorded in the motion data, there were no instances of undetected tennis stroke events or false positives when testing the algorithm on the small limited data set.

3.2.4 Swing Recognition Results

For the purposes of the swing recognition module, the presented novel algorithm (Table V-3), utilising a traditional algorithmic approach on the tennis data set, is capable of 100% accurate classification of tennis motion data sequences into two output classes namely ('forehand', 'backhand').

3.2.5 Experiment 2 Insights

The integrative modular design utilised in this research supported the concept of replaceable 'building blocks' to achieve optimised algorithm performance for a given (sport) discipline and application context.

As introduced in Chapter 2, existing event indexing solutions based on impact vibration or sound recognition for simple event indexing may be prone to false positives or failing to detect motion events[24]. Although such solutions may appear to provide the fastest computational solution, a hybrid solution – that is designed to compare results of diverse methods in parallel – may be more appropriate for future systems.

In line with the point of view that this thesis is a 'snapshot' in time that should provide a foundation for future systems, two otherwise peripheral requirements were achieved for this experiment:

1. Low extracted feature dimensionality and
2. A relatively fast computation algorithm that could be ported to future hardware (single and multi-processing) platforms.

The current tennis swing recognition implementation as a two stage modular design could be converted from its present computational model into a parallel, multithreading computation paradigm. The *sliding window* concept (Table V-4 and Table V-5) was optimised to suit a fast computational model of possible prerequisites for the existence of a *region of interest* interval whose parameter computation could be invoked as another parallel computational thread. It is also expected that with more motion data available from more diverse subjects the complexity of a future solution working on linearly non-separable data (e.g. computed hand velocity maximum) will warrant further research combining various neuro-fuzzy approaches.

3.3 Experiment Set 3: Adaptive Assessments and Evolving Principles

The aim of the third set of experiments embedded in this tennis case study was to demonstrate adaptive assessments of heuristics and coaching rules, subject to flexible criteria. The adaptive and incremental operational capabilities of ECOS support rule extraction at any point of the knowledge acquisition process. The flexible and modular architecture design adopted in this thesis enabled substitution of traditional classifiers (e.g. non-evolving RBF) with ECOS. As investigated on the tennis data set (Bacic, 2003a; Bacic & Zhang, 2004; Bačić,

[24] Also addressed in Chapter 7, data recording protocol and camera setup for experimental validation.

2006a), complex machine knowledge (e.g. as reflected in a large number of complex rules) extracted as in-principle human-comprehensible rules may still be difficult for humans to understand (Figure VI-8). However, while potentially difficult for human comprehension, this extracted machine knowledge can be saved as a ML snapshot in time and, when needed, inserted into a system as a preconfigured 'system start-up' machine knowledge, which can then continue to learn in an incremental and evolving fashion. This approach enables machine knowledge as flexible criteria to be kept externally in a database if needed.

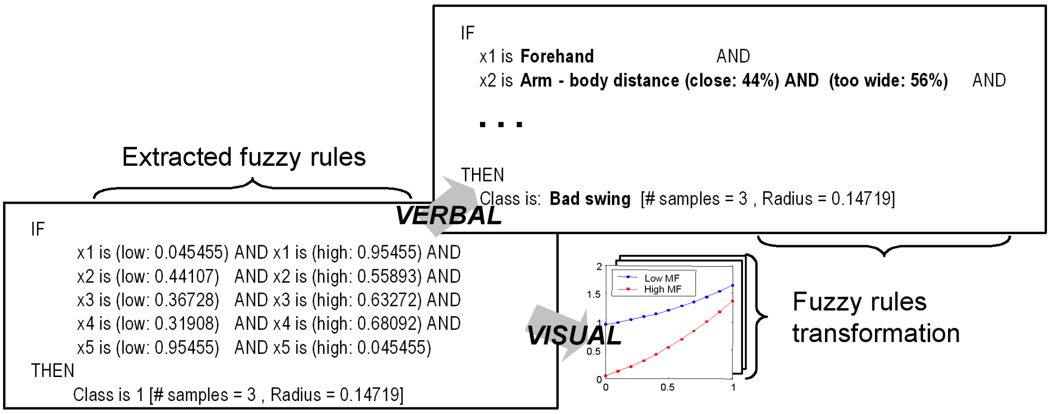


Figure VI-8. Example of (machine) extracted fuzzy rules and further verbal and visual transformations. Modified from (Bacic & Zhang, 2004).

Building on the human-understandable MoHEM/CREM diagnostic outputs as a functional concept, the experiments highlight the diagnostic principles on examples of a set of heuristics and coaching rules in tennis. Continuing from the previous two experiments, this set of experiments demonstrates the integration of proposed tennis coaching concepts, implementing practical evidence linked to the central focus of the thesis.

Note on experimental context of subspace modelling and MoHEM/CREM assessment orchestration:

Rather than attempting to translate holistic machine classification rules that govern the equivalent of qualitative human assessment of motion data, the philosophy of these investigative development case study experiments is in achieving machine-based alternatives to 'atomic' *assessment elements* (equivalent to taking a bottom-up approach) that are human-comprehensible and relatively easy to validate in isolation. Flexibility of assigning and choosing their importance is left to the end-user (a coach or learner). Adaptive mechanisms are demonstrable in the application of evolving connectionist systems, and in the flexible architecture enabling addition or removal of assessment elements without the need to manually re-do previous steps (e.g. retrain the network with previously stored data samples). Mathematical methods from CI can learn from data, evolve and generate internalised rules (Duch et al., 2004) constituting in the resulting machine inference (Kasabov, 2002).

As a software application, the prototype's purpose is to demonstrate proof of concepts, via the user interface Figure V-8 (Chapter 5), which is designed for users from different disciplinary backgrounds.

3.3.1 Coaching Rules in Embedded Case Studies

This embedded set of investigative development case studies utilised the existing database of extracted tennis swings (motion event samples) demonstrating the last stages of temporal and spatial filtering (see equation (V-2), Chapter 5):

- $f_T CR_i$ … temporal coaching rule (CR) region of interest
- $f_S CR_i$ … spatial computation within the region of interest.

A small set of CR was selected for prototyping and implementation to demonstrate principles central to the thesis and this case study, as set out in Table VI-5.

Table VI-5. Selected CR for prototyping.

CR-ID	Cue or CR	Rationale description
CR 2	'Square' stance – side body hitting position.	E.g. feet approximately parallel to the target line during the swing action phase.
CR 11	'Semi-open' stance – body position.	Assessed at intermediate skill level, a variation of a CR 2 assessment criterion.
CR 5	'Low to high' – swing path.	Controlling the ball's top-spin, ball flight and placement properties and margin for error. Cause and consequence reasoning.
CR 6	'Swing width' – wrist to body distance.	Safety vs. performance or 'reach' vs. margin for error.

Note: CR-ID is shown for reading convenience i.e. to visually match the numeric order of CR within the user interface (Figure V-8). Also a 'CR-ID data set' comprises extracted machine learning data associated with the accompanying coaching rule CR-ID.

Motivating factors for choosing the CR implementation candidates implemented in the initial prototype were as follows:

1. Required CR to be suitable for novice skill level criteria computation.
2. Low dimensionality of problem space relative to number of samples for validation purposes.
3. Simple and fundamental CR, logically acceptable to cross-disciplinary areas.

4. Demonstrability to wide cross-disciplinary areas for:
    a. Qualitative human observation and classification, and
    b. Automated-CR based classification.
5. Provide sufficient coverage of thesis concepts and application (e.g. performance vs. safety optimised assessment, discussed in Chapter 5).

The Stance Coaching Rules (CR 2 and CR 11) and Heuristic Context

The concept of *balance* has an important role in coaching tennis as well as in basic motor skills. Computationally assessing balance, as a problem area, would fit into the category of "problems for which there are no effective computational algorithms" (Duch, 2007), suggesting the consideration of connectionist methods or broader CI approaches. As a part of addressing balance, typically during initial tennis training sessions, learners are taught the 'square stance' (i.e. to hit the ball 'side-on' cue) assuming a side body position during the swing. As an open-skill endeavour, the game of tennis has evolved over the years of play from 'traditional' to 'modern', resulting in a shift in preference from 'square stance' to 'semi-open' stance (Crespo & Higueras, 2001; Knudson, 2008a). Although it is possible to see modern elite players hitting the ball 'on the run' from all positions (closed, square, semi-open and open) the semi-open position seems the most common in 'modern' tennis and it is typically taught after learning the square stance. Concepts also associated with balance include 'weight transfer' for different strokes, and static ('steady' position) and dynamic stance (hitting the ball on the run), and these are also commonly addressed in subsequent coaching scenarios.

The 'Low to High' Coaching Rule (CR 5)

The 'low to high' coaching rule is associated with ball spin heuristics. A 'low to high' hand movement (or 'brushing the ball' – cue) is important for controlling ball placement, speed and other properties of the ball's trajectory (Bahamonde, 2008). The 'low to high' movement as a swing segment can be a deliberate action or a consequential action occurring as a result of an individual backswing. Just as human players 'feel' and make adjustments during play, connectionist systems also have the potential to utilise supervised learning to differentiate swings into their specific assessment categories and can be emphasised or given less attention during coaching.

The 'Swing Width' Coaching Rule (CR 6)

The 'swing width' is typically not coached in isolation but it is normally communicated in feedback or coached as an intervention (Bollettieri, 2001). Due to the very high number of possible execution styles and grip preferences, it is expected that a coach may assess a player's 'swing width' but not to express it to his/her learners in absolute terms. Although tennis is an impact sport, most people do not appreciate the intensity and severity of ball impact/collisions on the body until there is an injury (Knudson, 2008b). Among the factors increasing the risk of injury, 'swing width' assessment criteria may also be influenced by a coach's familiarity with the learner and awareness of their recovery from injury. The 'swing width' may be assessed in a CR with the idea to improve safety or (in this case, mutually exclusively) to improve performance of the impact speed. In another example, in a CS for a return stroke practice it is a common expectation to extend the swing width to 'reach' the ball – within reduced reaction times but within the safety of a particular range of motion.

3.3.2 Data Analysis

Due to the presence of NaN values (as missing digitised marker locations) and the requirement for more marker tracks than in previous experiments, for this set of experiments and coaching rules, the data set comprised 43 samples (21 forehands and 22 backhands). Given the likelihood of unbalanced data set modelling problems (including three output classes for two tennis swings), data analysis included output class distribution and swing categories for each CR.

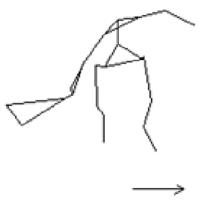
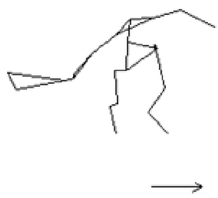
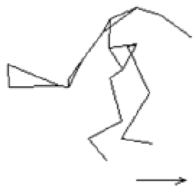
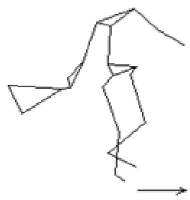
All expert labelling was performed retrospectively (justifying the need for *external synchronisation for visualisation and replay* in 3D) as for a coach it would not be common to assess 'stance', 'low to high' or 'swing width' relying on real-time computation of mathematical values e.g. static or dynamic feet angle during the swing.

Data analysis also incorporates qualitative interpretation of captured context. This provides an indication of whether the data set is representative of the target skill level's *data universe*, which is viewed as part of the subjective coaching experience captured in the human mind.

Data Analysis for Square and Semi-Open Stance Captured Context Interpretation

Table VI-6 illustrates different assessment criteria resulting in different output class data for 'square' CR 2 and 'semi-open' CR 11 stances.

Table VI-6. Stance visualisation examples and different output class assessment criteria.

Closed Stance (to a minor degree)	**Square Stance**	**Semi-open Stance**	**Open Stance**
			
Target line direction			
No. of samples: 15	No. of samples: 19	No. of samples: 4	No. of samples: 5
Output class	Output class	Output class	Output class
CR 2: 1	CR 2: 0	CR 2: 1	CR 2: 2
CR 11: 2	CR 11: 1	CR 11: 0	CR 11: 1

Where the output class of a coaching rule (CR-ID) is labelled as:
0 … very good
1 … average
2 … bad.

As each coaching rule and associated assessment criteria are mapped to different ML data sets, it is possible to see (Figure VI-9) that for the square stance there was balanced presence of 'very good' and 'average' positions, while for the semi-open stance the number of 'very good' swings appeared to be represented as a minority output class. Before concluding that the number of swings executed from a semi-open stance was a minority class it was necessary to undertake further data analysis of swing distributions, taking into account that more than half of the swings were single hand backhands, which were less likely to be executed from a semi-open or open stance compared to a forehand.

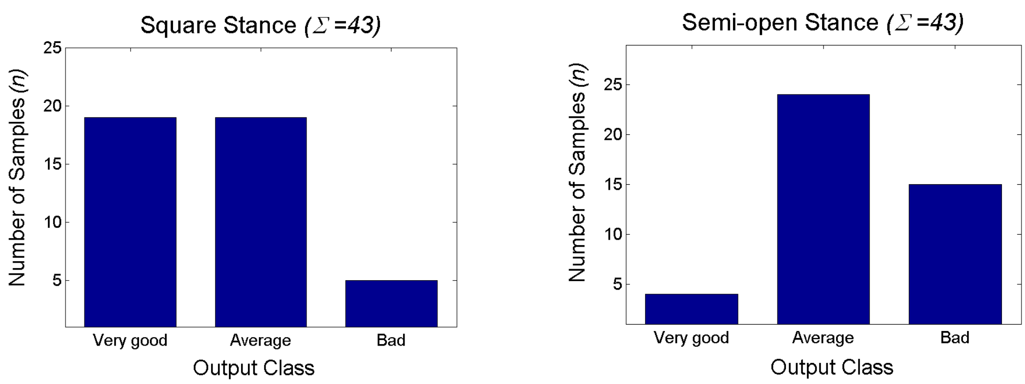


Figure VI-9. Comparing assessed output class distributions for square and semi-open stances.

Data Analysis of Swing Distributions and Interpretation of Captured Context

The following analysis provided visual information on swing distributions to indicate how well the acquired data set matched or represented the expected data *universe* and also to indicate possible unbalanced set modelling concerns.

(a)

(b)

(c)

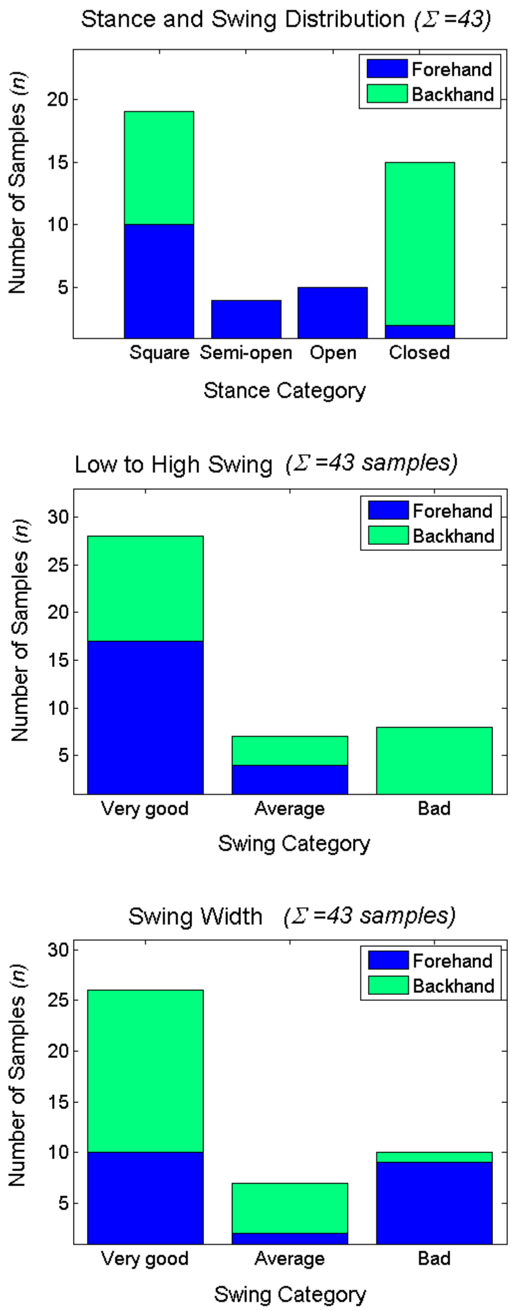


Figure VI-10. Tennis swings and distributions for: (a) Stance; (b) Low to high; and (c) Swing width.

Visual data analysis (Figure VI-10) from coaching and ML perspectives indicated the following observations from the available data set – intended to represent beginner to intermediate players' swings:

- Figure VI-10 (a) shows that forehand swings were executed from all stances, while single-hand backhands were executed from square and closed-stance. For forehand swings, a minority output class was evident for 'closed' stance swings. 'Square' stance was balanced to the aggregated set of 'semi-open' and 'open' stances;
- Figure VI-10 (b) infers that the 'low to high' swing segment action appeared to be easier to achieve with forehands than with single-hand backhands, for the target skill level of novice to intermediate-level players; and
- Figure VI-10 (c) infers 'swing width' bad output class would indicate wider swing (e.g. as a potential safety concern or desired increase in impact speed or extending 'reach'). As such, forehands were used more than backhands to execute variations of swing width.

The above insights drawn from the data analysis indicate that motion data contains captured context.

The interpretative insights associated with the 'low to high' (Figure VI-10 b) and 'swing width' (Figure VI-10 c) rules would represent new findings or knowledge discovery based on the data analysis, if it were to involve multiple players producing a sufficiently large data set to satisfy validity requirements. Together with quantitative data analysis the above interpretative insights could: (1) indicate if the available data set was representative of the expected *data universe*, and (2) confirm the feasibility of the intended motion data set modelling goals (see Chapter 4, Figure IV-10).

3.3.3 Coaching Rules and Feature Extraction Techniques

Temporal and spatial feature extraction techniques depicted in Figure IV-17 (Chapter 4) may be useful in facilitating generic concepts and specific implementation details or identification of insights of FET between interdisciplinary experts (Chapter 4). Together with Figure IV-17, Figure VI-11 provides visual evidence of the temporal transformation stage $f_T CR_i$ that occurs after swing type recognition $f_{TS} Sr_j$. Figure VI-11 shows visual evidence common to feature extraction algorithms for producing data sets CR-2, CR-11, CR-5 and CR-6 for machine classification on tennis motion data. All feature extraction algorithms producing data sets CR-2, CR-11, CR-5 and CR-6 were robust to minor missing marker values (Figure VI-11 b).

For example, for feature extraction oriented toward computing player stance:

- In Figure VI-11 (a) the time frames beyond computed index #26 indicate the hand marker was in front of the body (hand marker passed hip marker *SSGT* and virtual *'Body Centre'*) relative to the target line – which is known as the desired or intended impact zone start (a cue 'hitting in front of the body'), and can be utilised for ROI in which the stance is computed (see: Calculation of average angle as stance angle α between weight-transfer-moving-feet individual markers *PSM, SSM* positions in transverse plane, Step #5, Table V-6, Chapter 5); and
- In Figure VI-11 (b) the hip action movement pattern is common for a single-hand backhand in contrast to the forehand hip turn action around the body.

The feature extraction algorithm (Table V-6) for stance position (CR-2 and CR-11) is generic to racquet sports and so is provided in Chapter 5.

The input motion data for stance position CR requires five markers' time series:

1. PSGT … playing hand side great Trochanter
2. SSGT … opposite side great Trochanter
3. PSHD … playing side hand marker
4. PSM … playing side shoe tip marker
5. SSM … opposite side shoe tip marker.

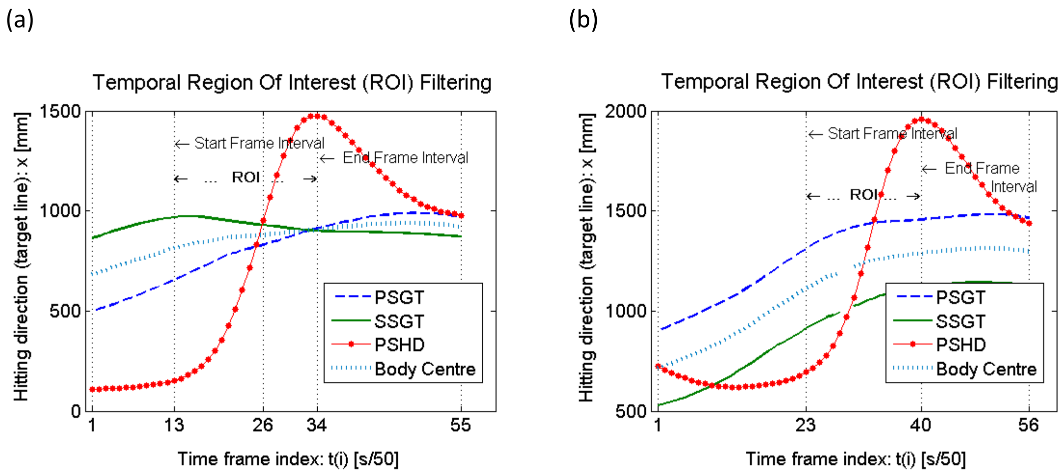


Figure VI-11. Temporal regions of interest computation examples during (a) 'steady', forehand and (b) 'step-in' single-hand backhand.

The feature space for stance position is two dimensional, containing the following variables:

1. Swing type (Forehand, Backhand). See generic algorithm in Table V-3
2. Feet Angle α, is relative to the target line during the initial part of a swing.

Temporal phasing was filtered from the beginning of a swing and before the impact zone. Spatial computation was demonstrable as the angle between the feet markers and the estimated target line. The estimated target line would be based on the rationale that a player from each side of the court can hit a parallel (along the line) or diagonal shot from an assumed stance i.e. once the stance is taken. A player's position on the court indicates an imaginary division between the preferred backhand and forehand hitting target angles.

The *feature extraction techniques* used in this thesis represent a novel concept, which is diverse from qualitative methods (Chapter 2) in terms of processing a subset of markers: (1) From diverse, non-adjacent parts of the body; (2) From not strictly bound observation/ROI processing of proximal-to-distal sequencing – from slow-moving to faster-moving segments; and (3) Using temporal sub-phasing that is not strictly bound to phases (preparation, action, follow-through).

The 'Low to High' Feature Extraction Technique and Insights

The algorithm for feature extraction of CR-5, the 'low to high' swing segment (Table VI-7) specific to captured tennis ground-strokes, ignored individual backswing motion but also extends computation of motion data through the action – impact zone.

The input motion data required the time series of three markers:

1. PSGT … playing hand side great Trochanter
2. SSGT … opposite side great Trochanter
3. PSHD … playing side hand marker.

Table VI-7. Swing path – 'low to high' segment feature extraction technique.

Swing path – 'low to high' CR-5

1: Initialise parameters and read filtered input data as a stroke (*Sr$_j$*)

$Sr_j = \{M(t) \mid t \in \{1 \ldots lastFrame\}, M \in \{PSGT, SSGT, PSHD\}\}$,

$\forall M = \{\overrightarrow{Xm}, \overrightarrow{Ym}, \overrightarrow{Zm}\}$, where $\overrightarrow{Xm}$ is marker's projection vector towards the target line

// Constant values depending on the capture frame rate of motion data

2: *EVAL_POINTS* = 6 as extended points for initial angle calculation

3: *MAX_CNT* = 5 as max. number of frames for minimal hand height relative to front hip

// Step #1. Expert's observation 'decision boundary' for stance angle compensation

4: *Swing* ← Tennis Swing Type Recognition(Sr_j) as in (Table V-3)

5: IF *Swing* = *FOREHAND* THEN

6: *Near_rear_hipM* ← *PSGT*

7: *Near_front_hipM* ← *SSGT*

8: ELSE

9: *Near_rear_hipM* ← *SSGT*

10: *Near_front_hipM* ← *PSGT*
11: END IF

//Step #2. Temporal ROI filtering – swing event

12: Extract Temporal Region Of Interest S_j [*startFrame*...*endFrame*; *PSGT, SSGT, PSHD*], where:

$$St_j \equiv ROI(f_T CR_i); St_j \subset Sr_j$$

$$St_j = \{M(i) \mid startFrame \le i \le endFrame\}$$

13: Calculate relative stroke displacement $\overrightarrow{Xstroke\_displacement}$ between the centre of the player's body as virtual marker 'Body Centre' and a player's wrist marker *PSH* towards the target as:

$$\overrightarrow{Xbody\_centre} \leftarrow \frac{\left|\overrightarrow{Xssgt} - \overrightarrow{Xpsgt}\right|}{2} + \begin{cases} \overrightarrow{Xssgt}, \overrightarrow{Xssgt} < \overrightarrow{Xpsgt} \\ \overrightarrow{Xpsgt}, \overrightarrow{Xssgt} > \overrightarrow{Xpsgt} \end{cases}$$

$$\overrightarrow{Xstroke\_displacement} \leftarrow \overrightarrow{Xpshd} - \overrightarrow{Xbody\_centre}$$

// Determine the Start and End interval as:

14: *startFrame* as a frame number ← $\max(\overrightarrow{Xstroke\_displacement})$ of the stroke Sr_j [1...*lastFrame*] at maximum displacement

15: *endFrame* as a frame number ← $\min(\overrightarrow{Xstroke\_displacement})$ of the stroke Sr_j [1...*lastFrame*] at minimum displacement

// Step #3. Further Temporal and Spatial filtering

16: Determine local minimum search and angle calculation and transformation as:

$$Sttr_j \equiv ROI(f_S CR_i) \circ ROI(f_T CR_i); Sttr \subseteq St_j \subset Sr_j$$

$$Sttr_j = \{M(i) \mid newStartFrame \le i \le newEndFrame\}$$

// CR detail – determine:
// 1) a ROI within [*newStartFrame, newEndFrame*] interval, in which hand marker *PSHD* has
// the lowest height and
// 2) when *PSHD* passes *Near_front_hipM* marker as *frontHip_i*

17: Determine distance vector as $(\overrightarrow{h\_dist}) \leftarrow \left|\overrightarrow{Xnear\_front\_hipM} - \overrightarrow{Xpshd}\right|$

18: Determine a frame number as *frontHip_i* ← $\min(\overrightarrow{h\_dist})$

19: Determine frame count relative to front hip *frontHip_i* and *local_min_i*, truncated within the boundary { *(–MAX_CNT)* ... *MAX_CNT* } as:
frameCnt ← countOffset(*frontHip_i, local_min_i, MAX_CNT*)

20: Determine a frame number of lowest height of hand marker as *local_min_i*← $\min(\overrightarrow{Ypshd})$

21: Determine $Sttr_j$ ROI interval as:

[newStartFrame, new EndFrame] ← *extendROI(local_min_i, EVAL_POINTS)*
by extending adjacent frame positions around *local_min_i*, containing additional number of *EVAL_POINTS* as in (Figure VI-12).

22: Calculate linear approximation expressed as:

line_Y=kX + n

within $Sttr_j$ of *PSHD* hand marker positions in sagittal plane x-y (see Figure VI-12) where:

$$\{\overrightarrow{Xpshd}[i], \overrightarrow{Ypshd}[i]\}, \{\forall i \in \Im \mid newStartFrame \le i \le newEndFrame\}$$

23: Calculate from linear approximation, initial low to high swing angle, as: $\alpha \leftarrow \arctan(kX)$

24: RETURN (*Swing*, α , *frameCnt*)

The resulting feature space is three dimensional, containing the following variables:

1. *Swing* … swing type (Forehand, Backhand)
2. α … initial swing angle
3. *frameCnt* … frame count of lowest hand position relative to front hip.

For the 'low to high' stage of feature computation, after determining ROI as a swing segment in which a hand passes the hip region, the sampling frequency for some swings was not sufficient to determine low to high approximation. To arbitrarily address this issue, in computing the CR-5 data set (consisting of all 43 samples), neighbouring frame samples were used to extend the ROI as shown in Figure VI-12.

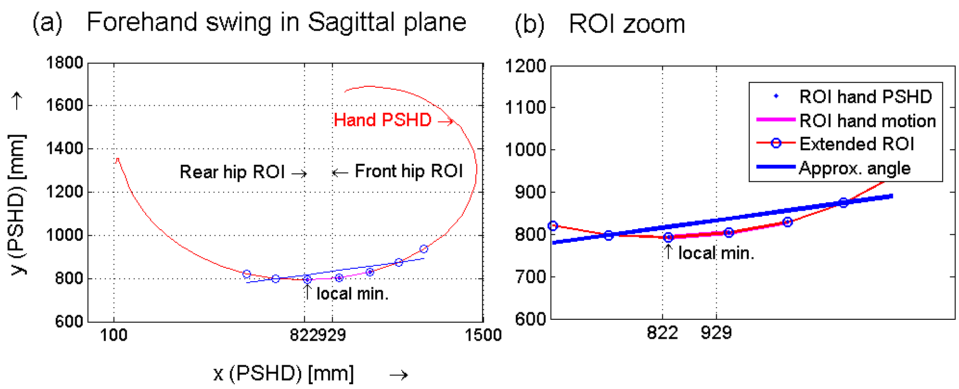


Figure VI-12. 'Low to high' temporal and spatial feature extraction of (a) forehand swing in sagittal plane and (b) ROI zoom.

The concept based on the idea of determining where the low to high movement starts relative to body position and intended impact would require a relatively high sampling rate, preferably superseding human vision for accurate detection and extraction of the swing properties of fast tennis swings. As for more complex variations of this algorithm, the desired sampling frequency would be higher with added ball impact information.

The 'Swing Width' Feature Extraction Technique and Insights

The algorithm for feature extraction of CR-6, 'swing width' (Table VI-8), also specific to tennis, results in three alternative output feature sets suitable for further classification investigation (note that the *body_height* in the experiment was preset to 1800 mm).

The input motion data requires three markers' time series:

1. PSGT … playing hand side great Trochanter
2. SSGT … opposite side great Trochanter
3. PSHD … playing side hand marker.

Table VI-8. Swing width feature extraction technique.

Hand to body swing distance – 'swing width'

Initialise parameters and read filtered input data as a stroke (Sr_j, *body_height*)

$$Sr_j = \{M(t) \,|\, t \in \{1 \ldots lastFrame\}, M \in \{PSGT, SSGT, PSHD\}\},$$

$\forall M = \{\overrightarrow{Xm}, \overrightarrow{Ym}, \overrightarrow{Zm}\}$, where $\overrightarrow{Xm}$ is marker's projection vector towards the target line

// Step #1. Expert's observation 'decision boundary' for stance angle compensation

Swing ← Tennis Swing Type Recognition(Sr_j) as in (Table V-3)

IF *Swing* is *FOREHAND* THEN

    Near_rear_hipM ← *PSGT*

    Near_front_hipM ← *SSGT*

ELSE

    Near_rear_hipM ← *SSGT*

    Near_front_hipM ← *PSGT*

END IF

//Step #2. Temporal ROI filtering – swing event

Extract Temporal Region Of Interest S_j [*startFrame*...*endFrame*; *PSGT, SSGT, PSHD*], where:

$$St_j \equiv ROI(f_T CR_i); St_j \subset Sr_j$$

$$St_j = \{M(i) \,|\, startFrame \le i \le endFrame\}$$

// Calculate relative stroke displacement $\overrightarrow{Xstroke\_displacement}$ between the centre of the
// player's body as virtual marker 'Body Centre' and a player's wrist marker *PSH* towards the
// target as:

$$\overrightarrow{Xbody\_centre} \leftarrow \frac{\left|\overrightarrow{Xssgt} - \overrightarrow{Xpsgt}\right|}{2} + \begin{cases} \overrightarrow{Xssgt}, \overrightarrow{Xssgt} < \overrightarrow{Xpsgt} \\ \overrightarrow{Xpsgt}, \overrightarrow{Xssgt} > \overrightarrow{Xpsgt} \end{cases}$$

$$\overrightarrow{Xstroke\_displacement} \leftarrow \overrightarrow{Xpshd} - \overrightarrow{Xbody\_centre}$$

// Determine the Start and End interval as:

startFrame as a frame number ← $\max(\overrightarrow{Xstroke\_displacement})$ of the stroke Sr_j [1...*lastFrame*] at maximum displacement

endFrame as a frame number ← $\min(\overrightarrow{Xstroke\_displacement})$ of the stroke Sr_j [1...*lastFrame*] at minimum displacement.

// Step #3. Temporal and Spatial filtering

Determine static swing width feature:

$$Sttr_j \equiv ROI(f_S CR_i) \circ ROI(f_T CR_i); Sttr \subseteq St_j \subset Sr_j$$

$$Sttr_j = \{M(i) \,|\, newStartFrame = i = newEndFrame\}$$

// Heuristic/ CR's detail – determine:
// 1) a ROI as [*newStartFrame = newEndFrame*] static interval, in which hand marker
//   *PSHD* passes *Near_front_hipM* marker as *frontHip_i* and
// 2) a minimal distance when *PSHD* passes a hip marker (i.e. *BodyM* algorithm variations)
//   as *frontHip_i*

Hand to body swing distance – 'swing width'

16: Determine distance vector as $\overrightarrow{h\_dist} \leftarrow \left|\overrightarrow{Xnear\_front\_hipM} - \overrightarrow{Xpshd}\right|$

17: Determine a frame number as *frontHip_i* $\leftarrow \min(\overrightarrow{h\_dist})$

// Determine static $Sttr_j$ ROI interval as:

18: *newStartFrame* ← *frontHip_i*
19: *new EndFrame* ← *newStartFrame;*
20: Calculate Euclidean scalar distance expressed as:

$$c = \sqrt{a^2 + b^2}$$

within static $Sttr_j$ ROI interval, where spatial feature extraction ROI within the frame *i* is:

$\{i = newStartFrame = newEndFrame\}$

$a \leftarrow XBodyM[i] - Xpshd[i]$

$b \leftarrow ZBodyM[i] - Zpshd[i]$

21: in transverse plane x-z as in (Figure VI-13) the static ROI require two points coordinates - defined as:

$$\{\overrightarrow{XBodyM}[i], \overrightarrow{ZBodyM}[i]\} = \begin{cases} \{Xnear\_front\_hipM[i], Znear\_front\_hipM[i]\} \Rightarrow \text{Dataset\_FET\_1} \\ \{Xbody\_centreM[i], Zbody\_centre[i]\} \Rightarrow \text{Dataset\_FET\_2} \\ \{Xnear\_rear\_hipM[i], Znear\_rear\_hipM[i]\} \Rightarrow \text{Dataset\_FET\_3} \end{cases}$$

$\{\overrightarrow{Xpshd}[i], \overrightarrow{Zpshd}[i]\}$

Resulting in algorithm variations are producing diverse output data sets for classification comparison are named:

(Dataset_FET_1, Dataset_FET_2, Dataset_FET_3)

22: Calculate conversation from absolute distance to arbitrary normalised, relative to players height as:

$$\delta \leftarrow \frac{c}{\frac{body\_height}{2}}$$

23: RETURN (*Swing*, δ)

The feature space and swing width alternatives:
Dataset_FET_1 ... front hip – hand
Dataset_FET_2 ... body centre – hand
Dataset_FET_3 ... rear hip – hand.

The feature space is two dimensional, containing the following variables:
1. Swing … swing type (Forehand, Backhand)
2. δ … swing width relative to the player's height.

For the swing width feature set CR-6, three experimental variations have resulted in different classification accuracy values using the same classifier and the same feature extraction algorithm. In addition to the *front hip* marker utilised in the spatial and temporal feature extraction for CR-2, CR-5, CR-6 and CR-11 (Figure VI-11) two other markers (*'Body Centre'* and *PSGT* in Figure VI-13) were investigated in order to improve classification accuracy in this case.

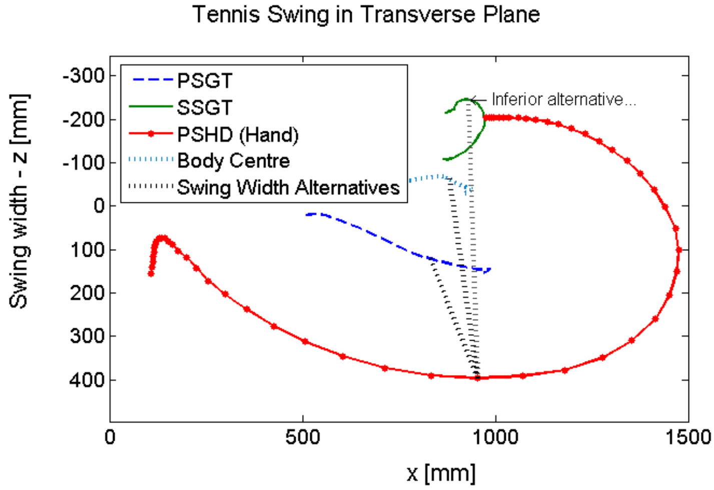


Figure VI-13. 'Swing width' and spatial ROI feature extraction.

For the experiment variations in which each of the additional two markers' motion data were used as an input, the same feature extraction algorithm produced a different data set. Note that in a coaching scenario where a coach is feeding the balls while facing a learner, it is typical to see the front hip, while e.g. in a square stance, the rear hip is occluded. The extracted features from the '*front hip*' motion data were found to produce inferior classification results (Table VI-9) when compared to extracted features from the '*rear hip* (*PSGT*)' or from the virtual marker '*body centre*'.

3.3.4 Classifier Modelling and Assessment Results

For small data set prototyping as encountered in the above scenarios, the selected modelling preference for the obtained feature sets (CR-2, CR-11, CR-5 and CR-6) was to utilise an evolving connectionist system with a minimal set of optimisation parameters using LOO cross-validation. LOO cross-validation was used because of the possibility that with unbalanced data, an entire minority class, due to random selection, could have been incidentally selected only for inclusion in the training or testing subset.

Table VI-9. Summary of classification results using LOO cross-validation and evolving clustering function (ECF) for embedded case studies.

Parameters	Classification results		
	CR-2 'Square' stance	**CR-11 'Semi-open' stance**	
E = 4; MF = 3, 2, 1.	91% OA; 39/43 correct.	91% OA; 39/43 correct.	
E = 1; MF = 2, 1.	88% OA; 38/43 correct.	88% OA; 38/43 correct.	
E = 1; MF = 3.	88% OA; 38/43 correct.	91% OA; 39/43 correct.	
	CR-5 'Low to high' swing		
E = 2, 3, 4, 5; MF = 3, 2, 1.	81% OA; 35/43 correct.		
E = 1; MF = 3, 2, 1.	60% OA; 26/43 correct.		
	CR-6 'Swing width': Front hip – hand (Dataset_FET_1)	**CR-6 'Swing width': Body centre – hand (Dataset_FET_2)**	**CR-6 'Swing width': Rear hip – hand (Dataset_FET_3)**
E = 4, 3 and 2; MF = 3, 2, 1.	81% OA; 35/43 correct.	**91%** OA; 39/43 correct.	**91%** OA; 39/43 correct.
E= 1; MF = 3.	**58%** OA; 25/43 correct.	67% OA; 29/43 correct.	72% OA; 31/43 correct.

Where:
CR-n = feature data set for the designated coaching rule; E = Epochs;
MF = Membership functions; OA = Overall accuracy.

Classification results were obtained using the Evolving Clustering Function (ECF) model in NeuCom Student ver. 0.919 (Song et al., 2008). Note that additional connectionist systems and validations were used and evaluated in Chapter 7 on the larger golf data set.

3.3.5 Experiment 3 Insights

The prototype system and its background processing capabilities using connectionist approaches were incrementally developed and tested using a relatively small data set. Classification results supported the system as providing a proof of concept solution to a 'theory-rich' problem area. With more data and further detected errors, follow-up design would enable the inclusion of additional coaching rules and feedback optimisation to support pedagogical principles in tennis skill acquisition.

It is also evident that MoHEM/CREM can indeed be trained as personalised, coaching scenario/group/skill-level or global assessment modules. Combining the flexible modular architecture with a data repository (Chapter 5) enables both online and off-line supervised training and the storing/retrieving of machine knowledge as snippets of time series matching coaching assessments and learners' activity. The system's autonomous operation is able to support diverse coaches' opinions, assessment criteria, training priorities and coaching scenarios.

Coaching Instruction and Feedback

Classification results for flexible assessment criteria on the experimental data (CR-2 and CR-11, Table VI-9) demonstrated the ability of evolving assessment modules to be trained using both subjective and flexible assessment criteria for 'square' and 'semi-open' stances.

The proof of concept and associated prototype performance demonstrated the novel automated assessment of qualitative diagnostic aspects of tennis ground strokes in a manner comprehensible for a coach and learner (as itemised diagnostics from MoHEM/CREM assessment output, Chapter 5). This was achieved via assessment of movement errors by collective classification operation of the enabled CREMs (see Figure V-8). The list of errors – or absence of them – may be presented as output labels and as colour-coded feedback. If required for the diagnostic outputs as feedback, presented as a list of movement errors, the list may be limited e.g. to display one item only, while the ACS system may generate a recommended intervention that is based on the list of movement errors.

Knowledge Discovery Contribution to Coaching

The data analysis reported in this chapter has indicated two potential knowledge discoveries related to 'stance' and 'swing path'. In addition, the associated 'swing width' CR-6 results obtained from all 43 data samples, lending greater certainty to this element of *knowledge discovery* and supporting 'swing width' assessment improvements in tennis coaching, injury prevention and competitive level playing. In terms of coaching, interpretation of the results of these machine automation experiments suggests improved assessment of 'swing width' for coaching scenarios when a coach facing his/her student is feeding the balls for swing practice. A coach should be taking into account the player's entire hip region instead of focusing observation on just the (non-occluded) leading hip during the swing action.

Linking Chapters 6 and 7 Case Studies

A pragmatic investigative development process oriented towards the goals of this case study justified the need for an interdisciplinary experimental design approach. A demonstrated proof of concept of the automation of qualitative tennis swing assessment was achieved and reported in this chapter. A flexible modular architecture supporting various coaching scenarios and criteria was combined with evolving connectionist systems to enable incremental and adaptive machine learning, flexible to the ever-evolving game of tennis.

Complementing this chapter as a main case study, the next chapter's investigative focus utilises connectionist approaches to modelling, data analysis and the introduced framework in a different sport domain. From a validation perspective, the next chapter leverages a relatively large data set with objective measures for outcome assessment – in the form of processed swing data obtained from the embedded electronics in a golf club instead of subjective assessment by an expert. The data set is associated with a single heuristic and is acquired in an outdoor golf driving range with multiple subjects striking a ball.

4. Chapter Conclusion

This chapter introduced the connectionist modelling and data analysis of human motion activity in tennis. Research outcomes and artefacts including generic ACS architecture components (Figure V-1, Figure V-2, Figure V-8), feature extraction techniques, classifiers, and the algorithms from Chapter 5, were combined with other elements specific to tennis. When applied to tennis data, background processing components (Figure V-1) – that learn from data or transform data) – were validated in this chapter. The demonstrated implementation of autonomous qualitative analysis in the form of automated assessment was mapped to diagnostic outputs that allow adaptable and evolving operation over time to support a coach and a learner. Diagnostic outputs based on subjective and flexible criteria were validated via *supervised learning* using an expert's diverse judgments on the same model and motion data. For example, computation of the 'stance' *coaching rules* was based on *supervised learning* utilising the two diverse output label data sets from judgments adhering to conflicting criteria for 'square' stance and 'semi-open' stances. In addition to this demonstration, the system was also able to accommodate flexible weighting of subjective *coaching rules* that can either be chosen or ignored – depending on the scenario.

Validation of the machine-equivalent modelling approach around the impact zone has resulted in high similarity to expert motion data evaluation when valuated holistically as 'good' or 'bad' swing technique. In addition to related work in biomechanics reporting on the curve fitting transformations related to impact zone and tennis ball interaction (Knudson & Bahamonde, 2001), for this experiment, curve fitting was simplified and to a degree 'over-smoothed'. Such simplified curve fitting of motion data to n-dimensional polynomial coefficients, as the features for autonomous ML operation, were still considered as not intelligible to humans. This also demonstrates that the system is able to operate in a separate problem space obtained from a high sampling rate and high precision, in contrast to human vision where an expert would observe an extended impact zone (i.e. swing kinematic chain) before assessing a swing. The 3D stick figure viewer and captured motion data can be utilised for visual assessment of technique.

Chapter 7

VII. A CASE STUDY OF MODELLING HUMAN GOLF ACTIVITY

The golf case study was focused on the use of the framework for motion data analysis and modelling (Chapter 4) and on complementing the tennis case study presented in the previous chapter. Preliminary experiments utilising some of the early augmented coaching systems for learning golf (reviewed in Chapter 2) provided valuable insights into technology-supported coaching and into supporting various coaching scenarios conducted on a driving range.

The connectionist approaches applied here demonstrate classification operation, or more specifically the prediction of a category of lateral deviation of ball trajectory relative to the target line, at the point of impact of a club face with a golf ball. This classification operation is based on collected biomechanical features relevant to the concept of a 'swing plane' – a heuristic referring to the 'ideal' plane of a golf swing. Key methodological concepts (as introduced in Chapters 3 and 4) are demonstrated through inter-subject real world golf data analysis and through the utilisation of specialised sport equipment infrastructure. These concepts include: data visualisation, pre-clustering and classification; feature space transformation and reduction, and rules generation that governs classification; and associated issues such as overlapping data clusters, unbalanced data and the feasibility of generating machine rules that could potentially be transferred to human coaching. While achieving relatively good classification results (around 89%) on an overlapping and unbalanced data set, reducing and presenting the machine generated rules to a human was considered infeasible due to the rules' dimensionality.

1. Introduction

The golf case study centres on the investigation of known heuristics of a 'swing plane' [25] and their relationship to predicting the characteristic club face path around the impact resulting in ball flight error from the desired target line. The real world data set was obtained in an unobtrusive manner, by using augmented coaching technology, with subjects hitting a ball with a driver club on a driving range. Being a relatively large data set (531 samples) acquired from multiple subjects (n = 13) it also enabled analysis of a variable set related to swing deviations from within the segments of an idealistic 'swing plane' and their importance relative to discriminating contribution properties to predicting ball flight category. In addition to data analysis, diverse connectionist models (evolving and non-evolving/traditional) were modelled, validated and compared in terms of their ability to classify the category of lateral deviation relative to the target line based on the 'swing plane' variable set that was obtained from the captured golf data.

1.1 Background

In contrast to golf course play, golf skills are often practised in controlled environments such as on a driving range. Practising golf on the driving range is considered a *closed-skill* sport (see Figure IV-6, Chapter 3). Contrary to the name 'driving' range, it is common for golfers to include into their practice golf swing variations using diverse golf clubs in addition to a driver. Other variations covered in the literature include (Hay, 1993b; Knight, 2004; Hume et al., 2005; Suttie, 2006; Keogh & Hume, 2012; Langdown, Bridge, & Li, 2012): functional vs. detrimental movement variability; constraint-led approach of employing swing parameter variability, and block vs. random practice coaching scenarios.

To promote a safe warm-up and to accommodate the 'feel' for different clubs, it is also common to start with shorter head-heavy clubs, and gradually progress towards longer clubs such as the driver.

By utilising augmented coaching technology in an assisted and supervised fashion, the experiment's context was to incorporate the driver's motion data capture and to create a positive learning experience as a part of a driving range learning routine, with a minimal degree of obtrusiveness. By utilising four or more driving range bays, a fixed equipment

[25] Described as a loosely defined concept of intended swing path, used in golf coaching.

setting and multi-subject pipelining, it was possible to combine individual progress with learning programmes and to capture relevant snippets of subjects' swing samples, in which subjects were utilising the driver only.

In contrast to the previous case study, the focus in this golf experiment was on a single heuristic, modelled on a larger data set originating from inter-subject data collection on a golf driving range with reference to real ball impact. Compared to Chapter 6, this case study investigation included some of the high-level, or more abstract, strategic and complex connectionist principles (introduced in the Chapter 2) requiring more available data but leading to more modelling-related insights.

1.2 Research Context and Experimental Design

The starting point for this case study was based on a critical review of the previous case study and on insights drawn from Chapter 2 – acknowledging the possibility of practical application of augmented sport coaching systems with multiple subjects. Further motivation and justification for this case study include the following:

- Applicable to multiple disciplines, the sub-space modelling concept can be demonstrated with a selected subset of features related to heuristics of a 'swing plane', therefore focusing this case study on a single heuristic associated with few dependent variables and their (relative) importance;
- The coaching scenario concept employing qualitative analysis can be supported by available augmented coaching technology ("SmartSwing," 2005; Leadbetter interactive," 2005), reviewed in Chapter 2. By combining the advantages of both technologies there is the possibility of a further usability study (common to the *human computer interaction* discipline) to develop or advance the next-generation technologies;
- An opportunity for study and validation of connectionist modelling and analysis of motion data from another sport discipline. Motion data would be collected in an unobtrusive fashion and in a 'natural' environment (outside of the lab) providing a relatively large motion data set of multiple subjects striking a ball; and
- Compared to the previous case study, conducting research on a larger data set would enable better generalisation, validation and meaningfulness of interpretation of analysis, to generate knowledge discovery applicable to sport, coaching and sport equipment.

Combining the approaches used in previously reviewed augmented technology systems ("SmartSwing," 2005; Leadbetter interactive," 2005) meant that the framework proposed here could support: golf learning, the qualitative observational cycle, CS, and introductory lessons (under human supervision and guidance). During and after the course of data acquisition, and as a result of observed technological shortcomings, additional tools were developed for coaching and analysis, including a video sequence player. The video sequence player has a similar interactive and presentation *'look and feel'* to the 3D viewer described in the previous case study, except for the 3D interactive virtual camera view. Appendix F lists additional tools developed by the author to support the research and experimental design in this thesis. The experimental design of this case study also included the following aspects:

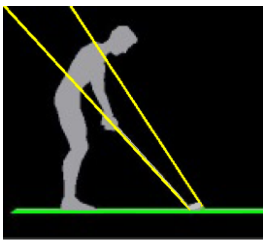
- Repeated measurements (golf driving range, the same driver and shoes), variation in subjects and their individual learning improvements; and
- Existing (standardised) methods in CI originating from statistics and connectionist methods for analysis, comparison, testing and validation.

1.3 Investigated Coaching Heuristic

The investigated coaching heuristic from SmartSwing ("SmartSwing," 2005) asserts that ball flight may be a consequence resulting from deviation of a golf swing from an ideal swing plane (Figure VII-1). In Figure VII-1 (a), the side (sagittal) view is:

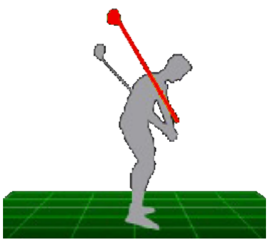
"showing the reference pro at address with a plane line extending through the club shaft (lower plane) and the other plane line going through the shoulder tip (upper plane)."

(a)



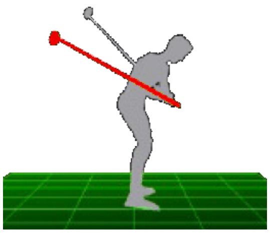
A **good swing** is one in which the club is on the lower plane line until it reaches a position roughly parallel to the earth. From this position, it moves upward until it is just under the upper plane line. The downswing should follow a plane roughly between the upper and lower plane lines.

(b)



The swing plane is too high or steep and therefore the club is over the top, above the plane line, on the downswing.
This may result in a **slice, fade,** or **pull**.

(c)



The club is too far inside (under plane) on the downswing.
This may result in a **hook, draw,** or **push**.

Figure VII-1. 'Swing plane' as a simple coaching heuristic, comprehensible to human reasoning. While the (a), (b) and (c) figures have minor modifications, the text shown in italics is originally cited from the SmartSwing software document (ImprovingYourSwing.pdf). The text highlighted in red in figure (b) represents output class (1) in the experiment while in figure (c) it represents output class (3). Output class (2) indicates a straight ball flight.

Although this case study is focused on analysis supporting the ACS framework (Chapter 4), a question based on the heuristics represented in Figure VII-1 is, can a machine also categorise the golf ball trajectory from captured real-life swing plane data?

2. Data Collection

Golf swing motion data were acquired using a SmartSwing driver golf club (consumer model LS300) of a common shape and 'feel'[26]. The club head is 400 cc titanium with a clubface loft of 10.5° and standard length, regular flex graphite shaft with embedded electronics in the handle of the shaft (see Figure VII-2, SmartSwing club electronic circuitry).

The club was designed to collect up to 100 swings of motion data in an off-line fashion and to transfer swing motion data to a PC. The club manufacturer claims:

> *"SmartSwing clubs record their position in space at 1000 times or more per second, over 30 times faster and more accurately than traditional consumer-based video systems. SmartSwing Intelligent Clubs use a series of gyroscopes and accelerometers in what is called a 6-degree of freedom inertial measurement unit."*
>
> (www.smartswinggolf.com/site/tic/science.html, accessed 23 Jul. 2009).

With reported sampling frequency of 1000 or more samples per second, and one hundredth of an inch resolution (in swing sample reporting), the SmartSwing augmented coaching system was designed to be accurate enough to measure specific differences in observed biomechanical features/variables in this experiment.

[26] Consulted NZ PGA affiliated expert was also able to confirm standard look and feel of a golf club, comparing SmartSwing with other drivers (without embedded electronic) after hitting the ball on a driving range.

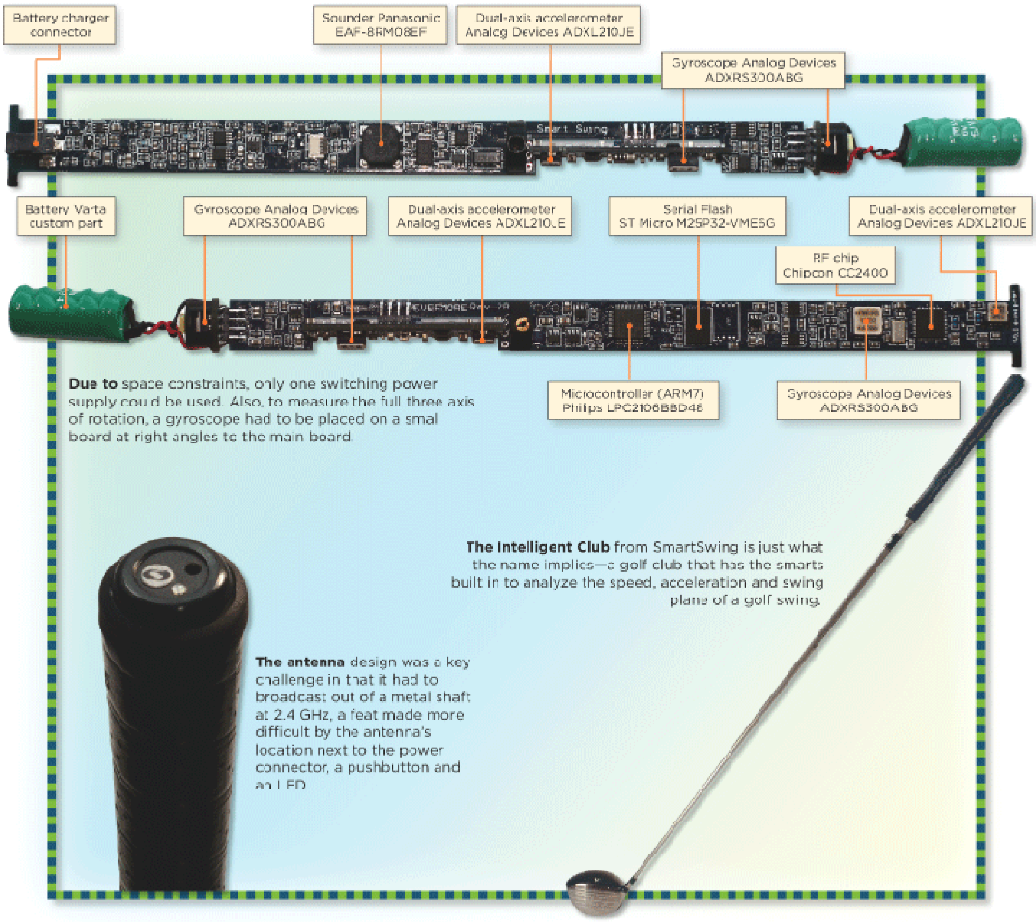
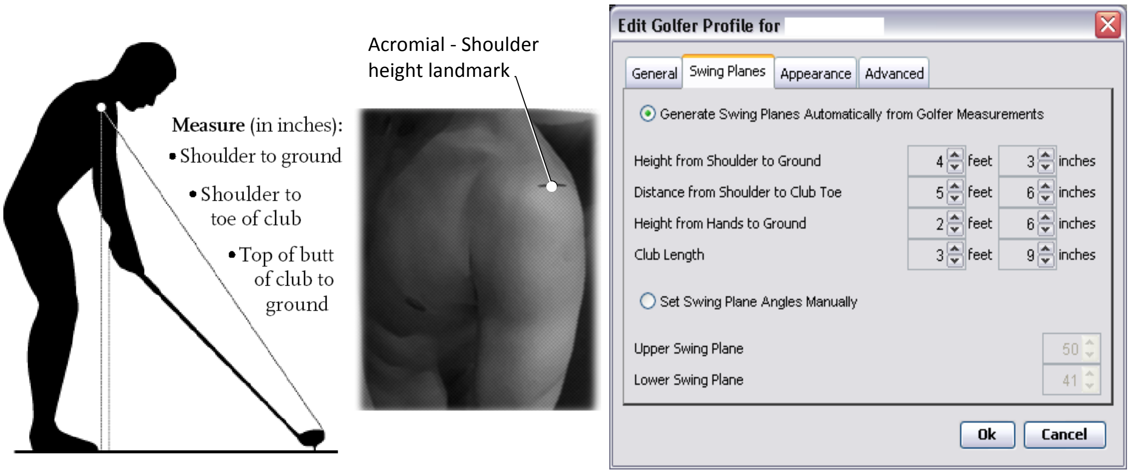


Figure VII-2. SmartSwing club electronic circuitry. Embedded electronics in the shaft of the club with further technical insights (Nass, 2005) are provided in the electronic article containing the Internet link to the image from above (retrieved 23 Jul. 2009, from http://i.cmpnet.com/eet/news/05/07/DC1386_TEARDOWN_PG_67.gif).

2.1 Experiment Setup and Motion Data

Before commencing data acquisition, the SmartSwing driver required the following: (1) sufficient battery recharge, (2) deletion of early recorded data and (3) initialisation specific to a user profile (Figure VII-3) via a software utility provided with the club.

Individual measurements and example parameters for a male subject of approximately 180 cm in height are shown in Figure VII-3. In the absence of more accurate instruction (from the club instruction manual) of the exact shoulder point, anatomical shoulder (acromial) landmark related measures were taken by the same researcher for all test subjects. In addition, each test subject had agreed prior to the experiment to wear the same golf shoes during the recording of profile measurements as well as during the entire experiment.



(SmartSwing Manual 2005, p. 5) SmartSwing Software

Figure VII-3. Subject profile information associated with the golfer's name required for SmartSwing software operation.

2.1.1 Camera Setup for Experimental Validation and Qualitative Video Analysis

In addition to SmartSwing motion data acquisition used in this *machine learning* experiment, the experimental setup also included video recording of golf swing data following the instructional guidelines from ("Leadbetter interactive," 2005).

Information from the video and SmartSwing system was used for: (1) Visual validation of recorded swings by the SmartSwing system; and (2) Qualitative analysis and communicating personalised individual feedback.

Each practice session was video recorded at approximately subject waist height from two perpendicular camera angles: (1) Towards-the-target line, behind the ball trajectory (i.e. allowing reviewing of the actual swing plane) pointing approximately at the hands during the addressing posture; and (2) A front view toward the centre of the subject's body (i.e. allowing a reviewer to see the key elements of stance and technique e.g. grip, top of the backswing horizontal variations and so on).

The distance between the cameras and the subject in each case was approximately 5 m, allowing vision of the club head throughout the entire swing motion with only minor distortions of the peripheral viewing of horizontal and vertical angles (e.g. fence poles – as reference to vertical angles), from the surrounding environment. The shutter speed was set to 'sport mode' (SONY® model DCR-TRV110E, high-speed shutter mode). The benefit of digital recording on a video tape is that it is possible to computationally extract a double frame rate (i.e. PAL interlaced standard allowing computational extraction from default 25 fps to 50 fps).

2.1.2 Coaching Programme for the Beginners

A coaching programme is included to illustrate learning progression for the majority of subjects without the emphasis on learning of a single heuristic such as a 'swing plane'[27]. The concept of a learning programme is in line with the augmented coaching system ("Leadbetter interactive," 2005) that was used in qualitative analysis of the recorded swings. The heuristics/coaching rules priorities (Table VII-1) and the learning programme for novices are provided in the Table VII-2.

Table VII-1. Heuristics/Coaching rules and feedback as subject learning priorities.

Priority and feedback focus	Remarks
1. Grip.	Lesson #1 ... Introduction.
2. Square stance: posture and ball addressing.	Lesson #1, 2, 3.
3. Swing motion.	Collected SmartSwing variables.
4. Ball impact: angle of attack; angle parallel to target line.	Output class for *machine learning* experiment from collected SmartSwing variables.
5. Ball flight.	Factors influencing the ball flight.

As a result of each lesson, the target number of collected swings was 10 – 30. The time intervals of golf swing recordings were dictated by each individual subject's comfort and pace. Lessons were internally divided into: 1) warm-up, 2) coaching information (including lesson objectives) and swing recording, feedback and 'homework' information and 3) cooling down and a stretching routine. Coaching and 'homework' information also included selected intervention routines from video analysis using ("Leadbetter interactive," 2005). From the subjects' perspective the last part of the warm-up routine involved (as semi-supervised by the researcher) hitting in the separate bays around 20-30 balls using different clubs, starting with

[27] Similar to "swing width" CR/Heuristics in Chapter 6, "swing plane" was not included as a session learning objective.

a heavier head, shorter shaft – preferably a sand wedge (SW) club. Subjects would receive minor corrections during the approximate 1 min. break after hitting 5-10 balls in a row. Subjects were also advised to take at least one day of rest between practice sessions and if possible, to also play or practise on their own. They were required to send email notes of their subjective learning experience before the next session. Such a teaching/learning strategy allowed: (1) Time for data processing and analysis, including reflection on subject email notes; (2) Subject's recovery and (3) Room for learning-by-doing at individual pace, reinforcing recently acquired feedback and learned motor skills in diverse environments.

Table VII-2. The coaching programme as an experimental activity. Subject learning was structured and focused on the main coaching rules (CR) and coaching (teaching topics) priorities.

Lesson	Introduced concept and focus	Remarks
1.	Introduction lesson: Grip, ball addressing and stance basics information (leg width and body alignment). Basic swing information.	Information pre-session included general and local driving range routine information, biometrics measurement for club initialisation and consent sign-off. Getting to know subjects and their relevant background. Making sense of basic technique.
2.	Stance focus: Posture and ball addressing. Hand and arms 'softness feel' Back swing (right knee and coil resistance) information	Upper body and knees corrections, technique corrections, comfort zone. Importance of using the large muscles (consistency) over small muscles (variations).
3.	Basic swing motion and dynamic posture stability: Focus on 'steady knees', hips, trunk and head.	Introduced wrist release, length of the swing, head, upper body and knees corrections. Visualisation and improving of achieving comfort zone.
4.	Ball impact: Angle of attack, swing path parallel to target line, speed information.	Introduced concept of ball flight trajectory being influenced by angle of incidence.
5. ...	Improving the ball flight.	Including individual intervention. Advanced beginner or higher skill level.

Information given to the subjects adhered to the coaching information from Leadbetter interactive learning ("Leadbetter interactive," 2005). The concept of progressing from beginner to expert and associated learning relevant to this study's perspective was introduced in Chapter 2.

2.2 Subjects and Golf Swing Data

Prior to the golf experiment, ethics approval for this component of the research (AUTEC number 06/105) was obtained from the AUT University Ethics Committee (Appendix E).

Subjects participating in the study were 13 golf learners, 5 females, 8 males, who ranged in age from 17 to 50+ years and in height from 157-181 cm. A sub-group of 10 beginners included 5 males and 5 females. The other 3 males in the sample represented those of intermediate to advanced skill level.

The data set available at the conclusion of the data collection sessions consisted of 531 golf swing samples (including 12 diverse golf swings captured from the 'demo user' included in the initial database with the SmartSwing club software ("SmartSwing," 2005) for analysis demonstration purposes). The remaining 519 swings were obtained from an original collection of 541 samples after removing the swings that were labelled as erroneous by the club software.

Captured data from the SmartSwing system database were exported to ASCII comma separated (CSV) text format for the purposes of the ML experiments and to overcome the two major constraints i.e: (1) The unavailability of a *software development kit* to access golfers' SmartSwing data; and (2) To adhere to the terms of the SmartSwing end-user licence agreement (SmartSwing Manual 2005, pp. 27-30), which prevented access to the internal workings of the club or to the system database.

To overcome these two major constraints, a set of stand-alone programs was designed to assist export from individual swing PDF data reports to the text based CSV data format suitable for use in the analysis environments used in this study (NeuCom, MATLAB and MS Excel; see: The supplementary CD, '02_Extract_Golf_Features_from_PDF_Scr_capture.m4v').

The next section of this chapter reports on modelling of the feature set comprising biomechanics values obtained from the SmartSwing golf club motion acquisition. All golf swing data used in subsequent computations were obtained solely from the unobtrusive SmartSwing system. No complementary data were added to the golf swing data set or were combined from alternative sources (e.g. video, microwave speed radar and the like). The golf club data were synchronised with video by: (1) The player profile selection in the club software; and (2) The player pressing the button for the first of the 5 consecutive swings. Video information contained the date, player and ball count information.

The 12 diverse golf swings from the 'demo user' (as the 14th golfer), containing eight swings with 'Parallel' output class, were not used for feedback, but to: (1) Help with modelling and analysis of the captured unbalanced data set; and (2) Provide data ambiguity reflecting real-life club usage by multiple player profiles.

3. Data Analysis

The swing motion data (Table VII-3) when transformed to the relevant problem space consisted of six input variables and one output class labelled as ranges ('Inside-out', 'Parallel', Outside-in').

In a form comprehensible to humans, the report format contained instances of 'name=value' and the units of measure. Where appropriate, a unit of measure was also provided with a descriptive form (e.g. computed output class labelled as 'Outside-in').

Table VII-3. Swing sample variables and values obtained from the SmartSwing system.

Swing sample data obtained from the SmartSwing system.	**Selected variables related to 'swing plane' for the *machine* learning experiment.**	
QUALITY OF SWING= 77% (Good)		
Tempo Meter=80% (Excellent)		
Swing Speed Quality=65% (Good)		
Quality of Plane=85% (Excellent)		
Top Club Speed=91.44 mph		
Top Speed Reached=14.1 in before impact		
Distance Lost=11.12 yards	**Selected Input Variables:**	
Swing Segment Chart # 2 = 3.53" inside	1. 'Swing Segment Chart # 2 '	*Backswing*
Swing Segment Chart # 3 = 20.09" inside	2. 'Swing Segment Chart # 3 '	*Top of the swing*
Swing Segment Chart # 4 = 3.27" outside	3. 'Swing Segment Chart # 4 '	
Swing Segment Chart # 5 = 18.54" inside	4. 'Swing Segment Chart # 5 '	*Downswing*
Swing Segment Chart # 6 = 1.51" outside	5. 'Swing Segment Chart # 6 '	*Top of the swing*
Segment #4=Across the line (42.2 degrees)	6. 'Segment #4'	
Length of Backswing=47.5 degrees Past parallel		
Impact Shaft Lean=1.5 degrees forward		
Angle of Attack=Descending (7.7 degrees)	**Output Class:**	
Angle of Incidence=Outside-in (5.2 degrees)	7. 'Angle of Incidence'	
Address Shaft Angle=30.6 degrees		
Address Shaft Lean=neutral (-0.6 degrees)		
Shoulder Plane=62 degrees		
Club Head Speed= 87 mph		
Est. Carry Distance= 207.92 yards		
Escape Velocity of Ball= 129.26 mph		
Tempo Ratio= 2.89:1		

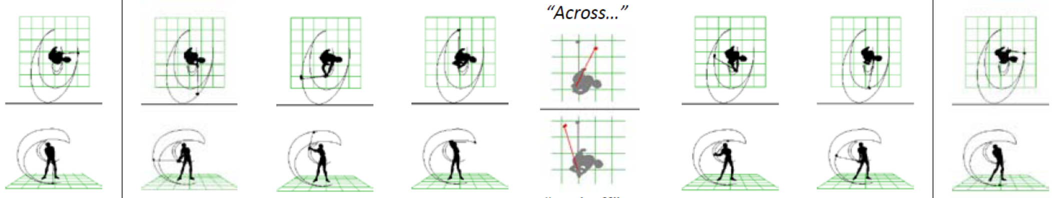
Note: The variable 'Length of Backswing' was not selected for this experiment because of the unclear and undocumented relationship to the swing plane.

In exporting non-discrete data from the SmartSwing system, where needed the values assigned to the first sub-category were multiplied by -1, denoting 'being short of' the ideal value. For example, the 'Segment # 4' value reported by the SmartSwing software could fall into three ranges or sub-categories: 'Laid-off', 'Parallel', 'Across the target line'. Values found to fall into the first sub-category during export were converted to negative numbers, while the other two sub-category values were left as reported by the SmartSwing system (to avoid overlapping values).

3.1 Problem Space Visualisation

A selected subset of variables from Table VII-3 is associated with the 'swing plane' heuristic and this is further depicted in Table VII-4.

Table VII-4. Swing plane variables visualisation in relation to a golf swing phasing. The thumbnail images were obtained from the SmartSwing application user interface and modified for viewing comparisons.

	Input						**Output**
Start Sequence	*Backswing*		*Top of the swing*		*Downswing*		*Ball Impact*
				*"Across..."* / *"Laid-off"*			
	Variable 1	Variable 2	Variable 3	Variable 6	Variable 4	Variable 5	Variable 7
N/A	Swing Segment Chart # 2	Swing Segment Chart # 3	Swing Segment Chart # 4	Segment # 4	Swing Segment Chart # 5	Swing Segment Chart # 6	Angle of incidence

The output class, angle of incidence, was known (Hay, 1993b; Suttie, 2006) to produce resulting lateral deviations from a desired direction (i.e. the target line).

An idealised conceptual model of ball trajectories was mapped to output classes from the SmartSwing system. The actual characteristic ball trajectories' curves and distance were occluded. Thus, the indicated output class could not indicate the actual ball flight direction but only a group of possible ball flight patterns (Figure VII-4).

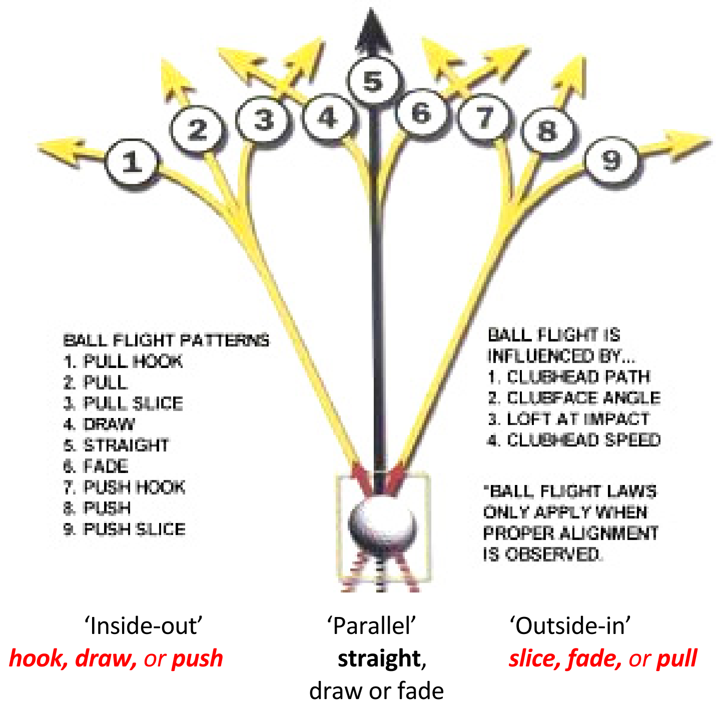


Figure VII-4. Conceptual model of golf ball trajectories mapped to output classes ('Inside-out', 'Parallel', 'Outside-in') used in this experiment. The conceptual model of golf ball trajectories figure was retrieved 23 Jul. 2009, from www.tutelman.com/golf/clubs/ballflight/theUsual.jpg).

Alternative figures including detailed descriptions of ball flight patterns and their classification can also be found in Suttie (2006, p. 12).

3.2 Feature Analysis, Evaluation and Clustering

Before attempting to design a classifier for swing angle of incidence based on swing quality (measured by a variety of characteristics), preliminary data analysis was undertaken to understand the wider context associated with the motion data relevant to this investigation (Figure VII-5). In this particular instance of the data analysis and modelling taxonomy (Chapter 4), which is related to golf activity, the issues addressed and the resulting outcomes comprised a combination of interlinked activities that were transferable between similar motion data contexts. For example, data analysis may reveal modelling challenges such as an unbalanced data set distribution relative to the output class, overlapping variable patterns and a possibility to extract rules from a connectionist system to inform coaching. While some classifiers could produce good classification results on balanced data, they may not be an optimal choice for unbalanced data sets.

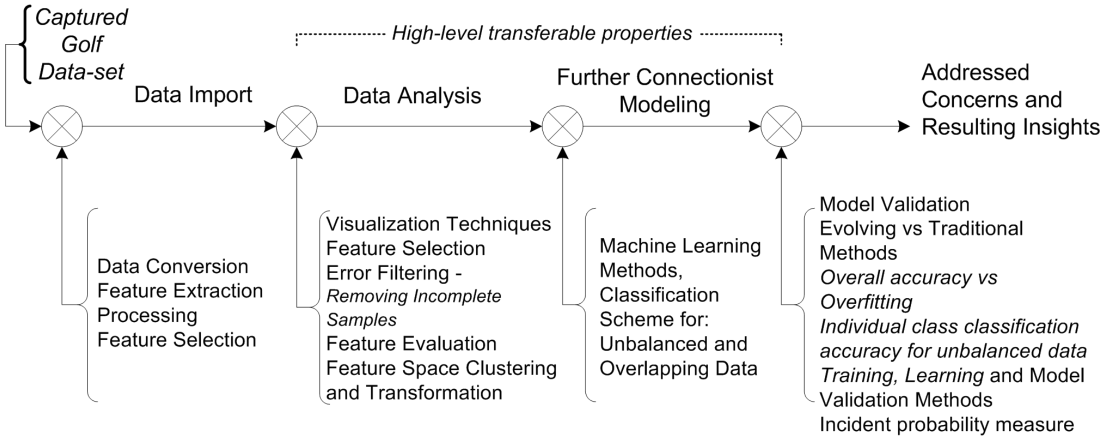


Figure VII-5. Related connectionist research contexts associated with the captured golf data set.

Data analysis may also include assessment of how each feature/variable might contribute to classification accuracy. Such an investigation could enable input space reduction if certain evidence was found e.g. diverse presence of noise in data variables, redundant positive or negative correlation between variables and how important each variable's role was to separate samples into corresponding output classes (also known as the discriminative property). Variable space reduction may also have resulted in a consequent reduction of complexity of machine-extracted rules. These rationales motivated the following investigation areas: 1) distribution of ball flight trajectory categories; 2) feature analysis – evaluation, selection and transformation linked to rule extraction as machine generated knowledge with data clustering; and 3) production of alternative golf data sets for further connectionist modelling/classification purposes.

3.2.1 Golf Data Set Distribution

A distribution of the output class 'Angle of incidence', as *knowledge of results* from the imported golf swing data, is shown in Figure VII-6. From a kinesiology perspective, it is important to note that the six input variables related to swing plane used in the experiment are not all that a golfer needs to consider in order to control ball flight patterns – there are a number of other factors (e.g. wrist release timing, shoulder angle, addressing the ball, involuntary mishitting the 'sweet spot' of the club face) that influence the outcome of a golf swing.

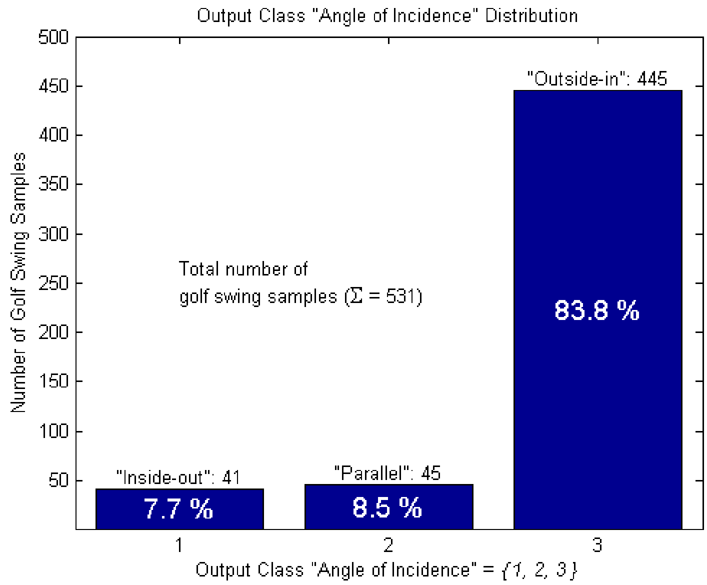


Figure VII-6. Unbalanced output class (1='Inside-out', 2='Parallel', 3='Outside-in') distribution. Analysis, calculations and figure visualisation were developed in MATLAB® ver 7.1.

Hypothetically, if in this challenge, for this unbalanced data set (Figure VII-6) a classifier would have only one rule (output='Outside-in", regardless of input) then its overall prediction accuracy would be 83.8%.

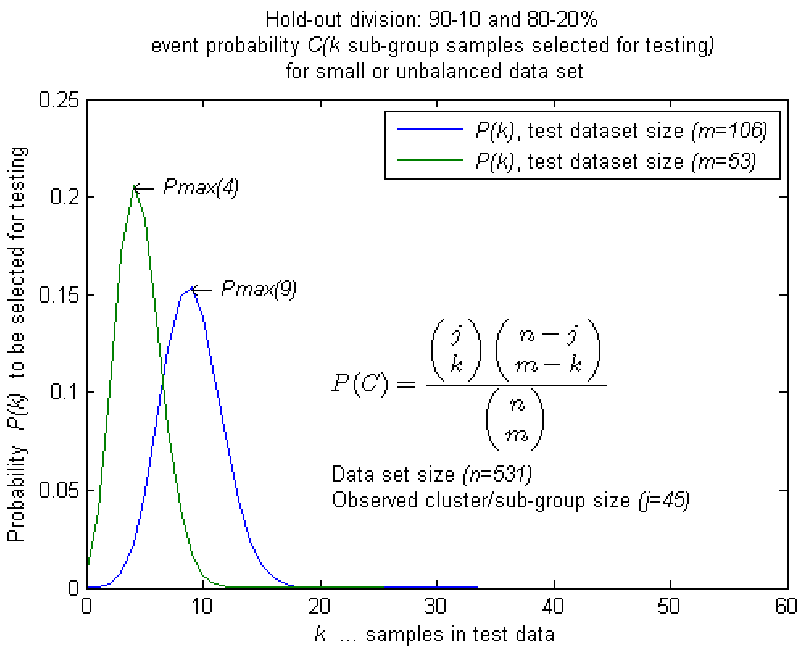


Figure VII-7. Example of probability of k samples from minority output class ('Parallel') to appear in test data set. Resulting calculations and visualisation were developed in MATLAB® ver 7.1. Formula (IV-1) that produced Gaussian bell shaped curve and parameters naming convention from Chapter 4 are additionally included in the graph for the reader's convenience.

In this case study, classification results included visualisations such as a 'confusion table' (e.g. an actual/predicted ['true positive', 'false positive'; 'false negative', 'true negative'] visualisation matrix) and a histogram of individual class classification accuracy. Further visualisation and analysis (Figure VII-7) included application examples of the novel formula (IV-1) aimed to prevent (or evaluate) probability of validation incidents (e.g. entire minority output class to appear in the test data set) for the golf data set.

3.2.2 Feature Analysis

Before attempting to design a classifier for swing angle of incidence, preliminary feature analysis was undertaken in order to assess how each feature (variable) might contribute to classification accuracy.

Correlation and Signal to Noise Ranking Comparisons and Variable Space Reduction

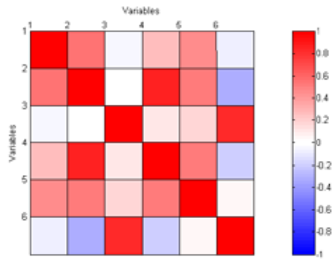
Introduced previously (Chapter 3) to indicate discriminative properties of the variables for classification purposes, both *correlation* and *signal to noise ranking* may produce similar results.
Because of the pairwise comparison nature of the tests, before attempting a classification on the full dimension data set, it may not be possible to know for certain how a variable would contribute to classification (e.g. cases of inter-dependence between the dependent variables). With this question in mind, creating alternative data sets representing a reduced original problem space can be used for classification comparisons or for the various strategic goals in augmented systems design (Figure IV-16).
Correlations and *signal to noise ratio* visualisations were produced using NeuCom (ver. 0.919 Student ed.). Numeric correlation testing (Appendix C, MATLAB sample code) using MATLAB™ ($P<0.05$) produced identical results shown in Figure VII-8. Correlation matrices indicated that variable pairs 2-4 and 6-3 respectively were more highly correlated than others (i.e. R=0.85 and 0.83 respectively) as highlighted in bold in Figure VII-8 (a). Related to the output variable 7 (Figure VII-8 b), the *signal to noise ratio* variable ranking (Figure VII-9) and pair wise numeric correlation variable ranking are, as expected, in the same order (Rvar[**5**-7]=0.56, Rvar[**3**-7]=0.32, Rvar[**6**-7]=0.31, Rvar[**1**-7]=0.15, Rvar[**4**-7]=0.1, Rvar[**2**-7]=0.03).

(a)

Numeric Correlation

Variable	1	2	3	4	5	6
1	1.00	0.56	-0.06	0.25	0.45	-0.07
2	0.56	1.00	0.00	**0.85**	0.52	-0.34
3	-0.06	0.00	1.00	0.12	0.16	**0.83**
4	0.25	**0.85**	0.12	1.00	0.53	-0.19
5	0.45	0.52	0.16	0.53	1.00	0.04
6	-0.07	-0.34	**0.83**	-0.19	0.04	1.00

Colour-coded Visualisation



(b)

Numeric Correlation

Variable	1	2	3	4	5	6	7
1	1.00	0.56	-0.06	0.25	0.45	-0.07	0.15
2	0.56	1.00	0.00	0.85	0.52	-0.34	0.03
3	-0.06	0.00	1.00	0.12	0.16	0.83	0.32
4	0.25	0.85	0.12	1.00	0.53	-0.19	0.10
5	0.45	0.52	0.16	0.53	1.00	0.04	**0.56**
6	-0.07	-0.34	0.83	-0.19	0.04	1.00	0.31
7	0.15	0.03	0.32	0.10	**0.56**	0.31	1.00

Colour-coded Visualisation

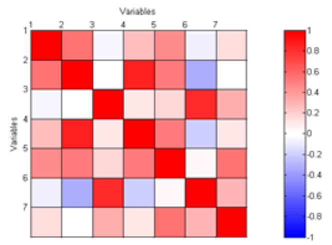


Figure VII-8. Numeric correlation of the problem space. Matrix in figure (a) shows pair-wise correlation between input variables, while the matrix in figure (b) reveals how the input variables were correlated to the output ranking, for comparison to *signal to noise ratio*.

Since the data set was not highly dimensional (relative to its data set size) the correlated results (denoted as Rvar[**n**-m] values) exhibited an identical order to the *signal to noise ratio* ranking. Both correlation and SNR analyses suggested that variable 5 or variables 5, 3 and 6 were related to variable 7, but because variables 3 and 6 were also mutually related (highlighted in bold in Figure VII-8 a), variable 5 or variables 5 and 3 seemed to be suitable candidates for further modelling on a reduced data set (not included in further investigation). Since one of the goals of efficient processing is space and rule reduction, variable 5 (the last downswing segment) and variable 2 (a segment, before the top of the swing) were chosen as an alternative 'best' and 'worst' (one input variable) golf data sets (noted as data sets #2 and #3, in Table VII-5) for comparison purposes.

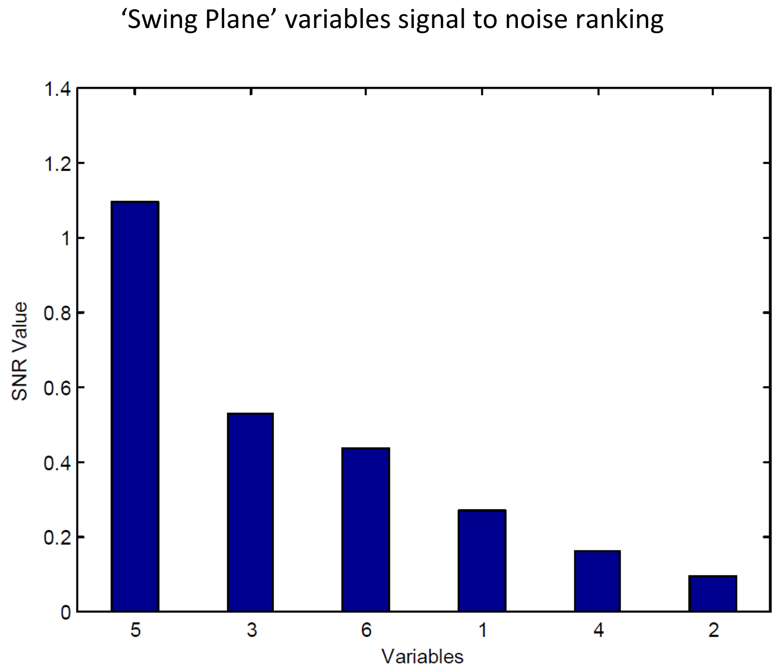


Figure VII-9. SNR ranking of input variables (NeuCom ver. 0.919 Student ed.).

While the variable 5 ranking, as expected, confirms the importance of the point of impact (linked to the Chapter 6 global model), it may be relevant for golf coaching to note that variable 4 (early downswing segment) did not follow variable 3 (top of the swing) in the *signal to noise ranking* order.

Data Clustering

To enable comparison and interoperability with diverse connectionist systems, and for clustering visualisation, the golf data set was linearly normalised within the interval [0…1] (see equation (III-1), Chapter 3).

While quantitative data clustering may indicate data patterns, cluster boundaries may or may not be similar to an expert's grouping as delivered through expert-based clustering (e.g. cognitive Gestalt-based grouping). The results of golf data clustering showed how the data could be grouped together based on mathematical similarity (e.g. distance-based grouping of n-dimensional space). Coloured samples (in NeuCom ver. 0.919 Student ed.) indicate overlapping data clusters (Figure VII-10).

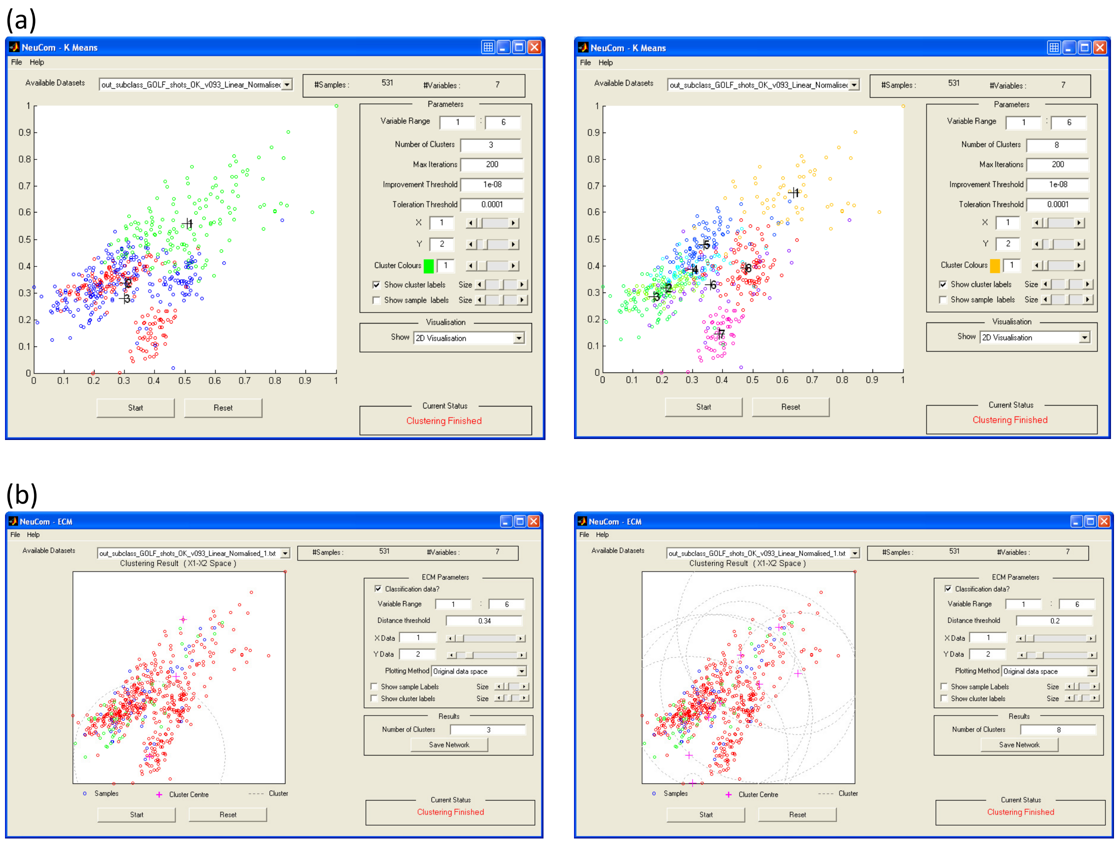


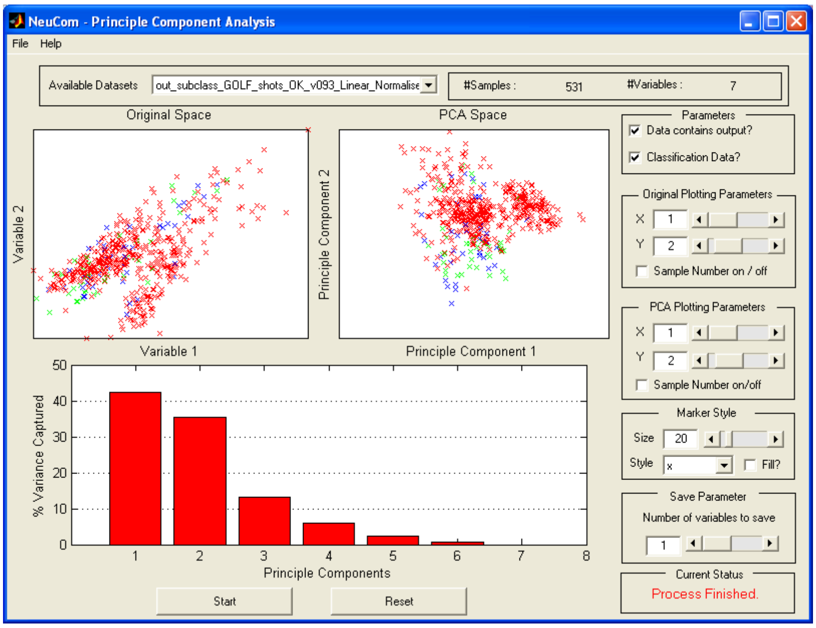
Figure VII-10. Clustering visualisation as part of the *machine learning* data analysis (NeuCom ver. 0.919 Student ed.). For figure (a) k-means clustering technique, the number of clusters is predefined before the start of computation. For figure (b) *evolving clustering method* the number of clusters depends on a predefined distance threshold (0.34 for 3 clusters and 0.2 for 8 clusters) and it evolves in adaptive fashion based on incoming data.

'Swing Plane' Feature Space Transformations and Reductions

In addition to the SNR variable ranking and correlation analysis that may inform variable space reduction (described above), the following two methods – *principal component analysis* and *linear discriminant analysis* work on the principle of transforming a variable space into a new, lower dimensional space (e.g. Figure VII-11).

The expectation that the new space may lead to better generalisation of an associated classifier model is based on increased data separation comparing the original data space with the new transformed space (created by one of the two methods). The rationale is also based on the assumption that transformed variables that are ranked lower may contain noise. Excluding noisy variable(s) from the problem space as redundant dimension(s) could therefore lead to both improved general classification accuracy and operation on reduced feature set dimensionality. In contrast to that assumption, if a classifier shows higher classification accuracy than expected on small to mid-sized noisy data sets it is possible to assume that any desired increase in generalisation classification accuracy may in fact occur due to potential overfitting (discussed in Chapter 4).

(a)



(b)

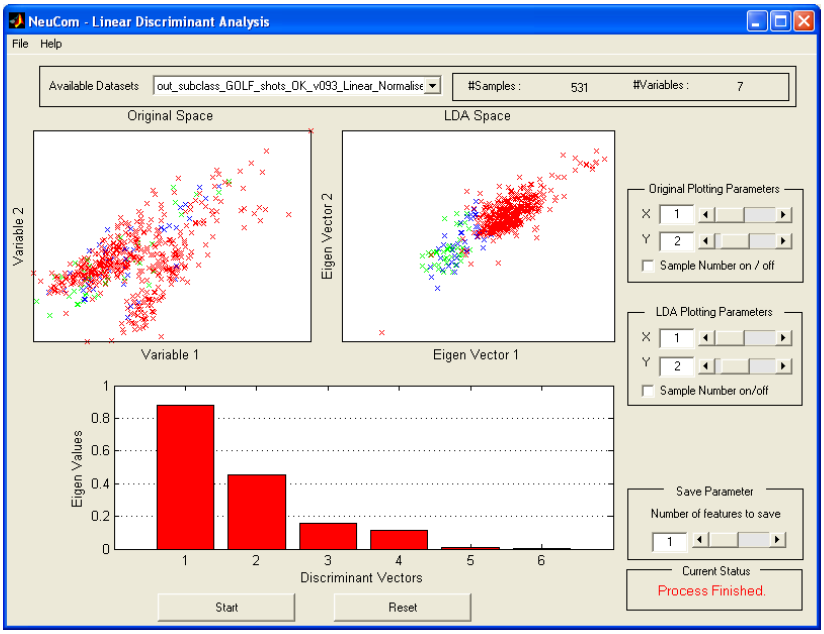


Figure VII-11. (a) *Principal component analysis* and (b) *linear discriminant analysis* transformations and analysis (NeuCom ver. 0.919 Student ed.).

When applied to the golf data set, both *principal component analysis* and *linear discriminant analysis*, as expected, demonstrated improvements in reducing the overlap between transformed components (new variables) that contributed the most to the variations of the computed data set (Figure VII-11). One of the reasons why *linear discriminant analysis* (Figure VII-11 b) could have resulted in better performance of expected factors (separation, variation and noise) than *principal component analysis* is because *linear discriminant analysis* computation takes into account both input and output space (i.e. output class, the supervised learning concept), while *principal component analysis* works on the input space only (i.e. the unsupervised learning concept).
As a modelling decision, in addition to the original golf data set, two *linear discriminant analysis* transformed and reduced dimensionality spaces were used (noted as data sets #4 and #5, Table VII-5) for classification comparison purposes, where needed.

The key issues identified from feature analysis here, were: 1) Unbalanced *knowledge of results* data; 2) Overlapping variable patterns; and 3) Rule extraction (surrounding 'swing plane' heuristics) as machine generated knowledge.
As a result of the analysis, research in this case study included a classifier modelling to achieve a relatively high degree of classification accuracy on an unbalanced data set, but also to provide insights into a wider context extending to motion data modelling (including model validation on alternative golf data sets, with reduced dimensionality where needed) linked to the augmented coaching system design.

3.3 Alternative Golf Data Sets for Diverse Modelling Objectives

Diverse modelling objectives (Figure IV-16) for predicting the characteristic golf ball trajectory included: fast computation, rule extraction and rule reduction intended to inform coaching. For the purpose of comparative analysis, alternative data sets (Table VII-5) were created from the original golf data set.
For **fast computation** and **extracted rule simplification**, variable 5 was chosen as the most suitable candidate to substitute and simplify the six-input-variable data space with a single variable input space. Both *signal to noise ratio* and *correlation* ranked variable 5 (last downswing segment) as the most strongly contributing single factor, and variable 2 (before top of the backswing) as the least contributing single factor to the classification inference.

Table VII-5. Data sets provided for classification after data analysis investigations. All data sets originated from the golf data and were modified to suit diverse modelling goals (Figure IV-16).

Data set #	Rationale
1. Golf data set, linearly normalised.	Main golf data set. Normalised ([0 … 1] interval) for operation with a variety of existing models and approaches.
2. Golf data subset, variable 5.	Can a single variable model result in a reduced set of extracted rules with minor decrease in classification accuracy?
3. Golf data subset, variable 2.	Verifying if preliminary data analysis (*signal to noise ratio* Figure VII-9) would indicate an expected decrease in classification accuracy and/or expected increase in the number of extracted rules compared to the results from data set #2/variable 5.
4. Golf data set LDA space converted, two new variables.	*Linear discriminant analysis* (supervised) transformation results outperformed *principal component analysis* (unsupervised). Selected two most significant new variables (Figure VII-11) for classification comparisons. Both methods may result in removing noise from data and provide potential for better class separation and classification accuracy then in data subsets (Data set #: 2 and 3). Can reduce dimensionality of space and still produce good comparative classification accuracy.
5. Golf data set LDA space converted, four new variables.	Possible improvements in classification accuracy than from golf data subsets (Data set #: 2-4). Selected four most significant new variables (Figure VII-11) for classification comparisons.

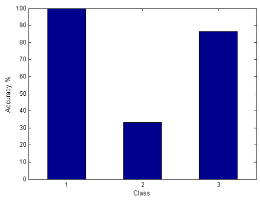
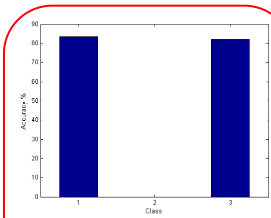
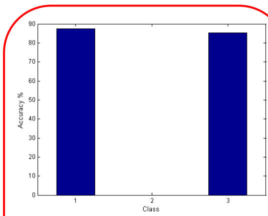
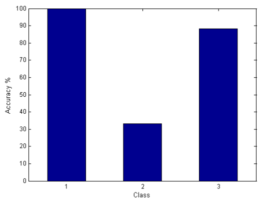
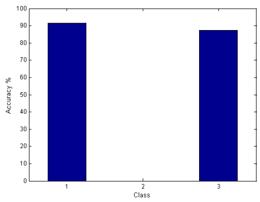
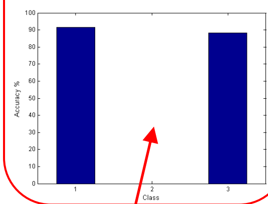
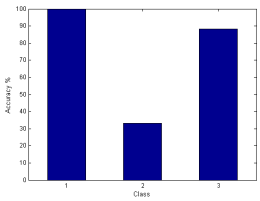
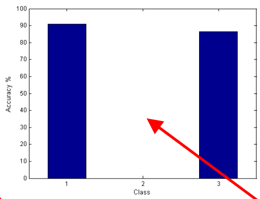
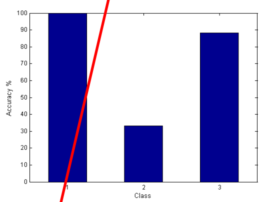
The last two data sets (#4 and #5, Table VII-5) were considered as **not suitable for rule extraction to human coaching** due to: (1) The complexity of the *linear discriminant analysis* (or *principal component analysis*) transformation to inform coaching or learning; and (2) Operating requirements (e.g. direct transformation) for future on-line operation.

4. Classification Results

In addition to employing common classification models (RBF, SVM) as reviewed in Chapter 2, this case study also reported ECF modelling in more detail, where needed. This included: evolving clustering, rule extraction, and on-line (one epoch) and off-line (multi epoch) batch optimisation. Supporting concepts for ECF (also revised in Chapter 2) were that clustering techniques could be used for classification if the output class was associated with each cluster and that such underlying connectionist structures could be used for rule extraction. Although not intelligible for human reasoning, the large number of generated clusters (nodes) as extracted machine rules may indicate more sub-rules and specific swing patterns than described in the 'swing plane' heuristic (Figure VII-1). As an indication of whether the 'swing plane' heuristic can be implemented in a machine, classification results were obtained using a *holdout* validation (see Table III-2) on traditional ANNs and a newer ECOS (i.e. SVM (Table VII-6), RBF (Table VII-7) and newer ECF (Table VII-8). Given the available unbalanced data set, the results included *individual class accuracy histograms* or *confusion tables* (see also Appendix B).

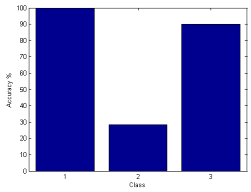
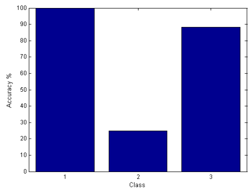
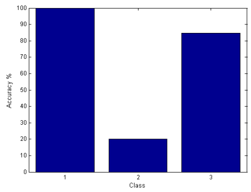
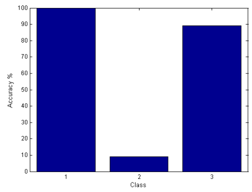
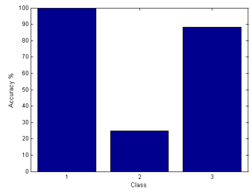
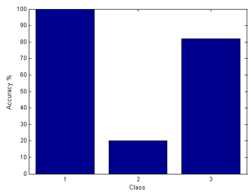
4.1 Traditional ANNs Classification Results

Table VII-6. SVM classification accuracy for 80-20% holdout, using golf data and *linear discriminant analysis* (LDA) transformed data sets with reduced dimensionality.

		Overall accuracy and individual class accuracy visualisation		
Model	**Parameters**	Data Set 1 All golf data set variables	Data Set 4 LDA - 2 variables	Data Set 5 LDA - 4 variables
SVM	Kernel:			
	linear	Overall accuracy = **85.85%** 	Overall accuracy = 82.08% 	Overall accuracy = 83.96% 
	polynomial, 2 deg.	Overall accuracy = **87.34%** 	Overall accuracy = **87.74%** 	Overall accuracy = **87.74%** 
	polynomial, 3 deg.	Overall accuracy = **87.74%** 	Overall accuracy = 86.79% 	Overall accuracy = **87.74%** 

Poor classification for minority class

Table VII-7. RBF classification accuracy for 80-20% holdout, using golf data and linear discriminant analysis (LDA) transformed data sets with reduced dimensionality.

		Overall accuracy and individual class accuracy visualisation		
Model	**Parameters**	Data Set 1	Data Set 4	Data Set 5
RBF	Training cycles = 100 Linear output function	All golf data set variables	LDA - 2 variables	LDA - 4 variables
	No. of hidden nodes = 36	Overall accuracy = **86.79**% 		
	No. of hidden nodes = 21	Overall accuracy = **86.79**% 		
	No. of hidden nodes = **12**	Overall accuracy = **82.07**% 	Overall accuracy = **81.13**% 	Overall accuracy = **86.79**% 
	No. of hidden nodes = 6	Overall accuracy = 79.24% 		

Note: Overall accuracy is provided to 2 decimal points for comparative purposes.
The histograms provide insight related to classification accuracy of individual output classes, which was relevant for the minority classes.

Further experiments using ECF included: (1) rule reduction and (2) cross-validation. The overall classification accuracy ε (see equation (VI-2) used in Chapter 6) was the ratio between the number of correctly classified examples and the number of all examples from the input data. All classifications with associated visualisations and validations were produced using NeuCom (ver. 0.920 Student ed.).

As an observation from Table VII-6 (SVM), the best results were achieved using a 3rd degree polynomial SVM kernel. For the same kernel, alternative 'Data Set 5 LDA - 4 variables' containing reduced dimensionality (4 new/transformed variables) produced identical classification results. Minor classification decline was noted with less complex kernel settings. Regardless of the SVM kernel, the original data set provided the best overall classification results for the minority class ('straight' impact).

As an observation from Table VII-7 (RBF), the number of hidden nodes and their impact on overall accuracy is difficult to estimate. The increase from 21 to 36 hidden nodes did not result in improving overall accuracy – suggesting possible model overfitting.

Because of minor classification accuracy improvements of the RBF relative to incremental parameter change, only one experiment (12 hidden nodes – as a possible sub-optimal model) included classification results using alternative data sets. For that case, RBF performed better when using a transformed data set ('Data Set 5 LDA - 4 variables'). Another observation specific to RBF was that even with relatively lower overall classification results compared to SVM, the RBF was still working relatively well with the minority classes of the supplied unbalanced data set.

For the purpose of extracted rule reduction, alternative data sets #4 and #5 were replaced with #2 and #3 in the next classification results.

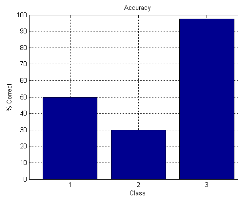
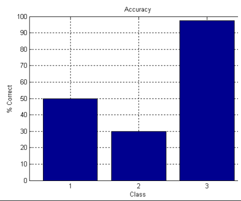
4.2 Classification Results Using Evolving Classifier Function

ECF classification accuracy for the original data set only indicated the highest overall accuracy for both one-pass online and for four epochs off-line modes (Table VII-8).

The class that was most susceptible to misclassification with all classifiers (SVM, RBF and ECF) was class 2 'straight shot'.

Although delivering the highest accuracy and the fastest model, ECF showed lower classification accuracy for class 1 than the other classifiers.

Table VII-8. ECF classification accuracy for 80-20% holdout, using the golf data set.

		Overall accuracy and individual class accuracy visualisation		
Model **ECF**	**Parameters**	Data Set 1 All golf data set variables	Data Set 4 LDA - 2 variables	Data Set 5 LDA - 4 variables
Max field=1 Min field=0.01 MoN=3 MF=2	No. of epochs = 4	Overall accuracy = 90% At 80 Rule nodes 		
	No. of epochs = 1	Overall accuracy = 90% At 69 Rule nodes 		

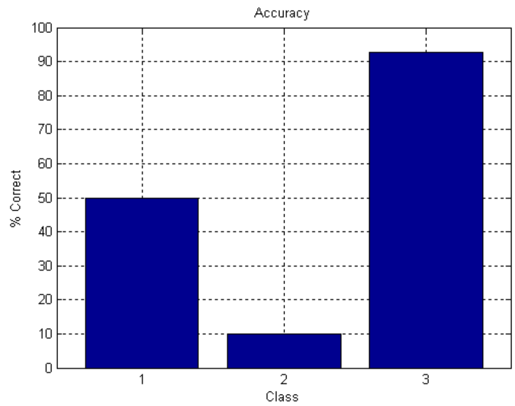
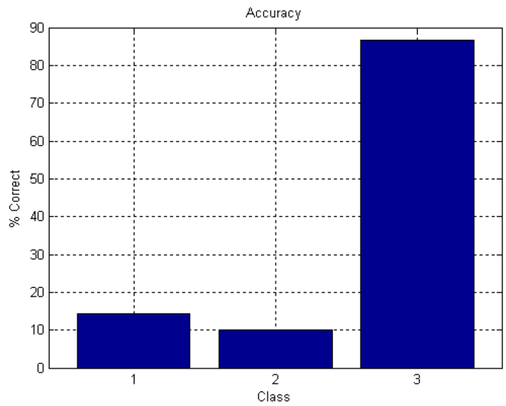
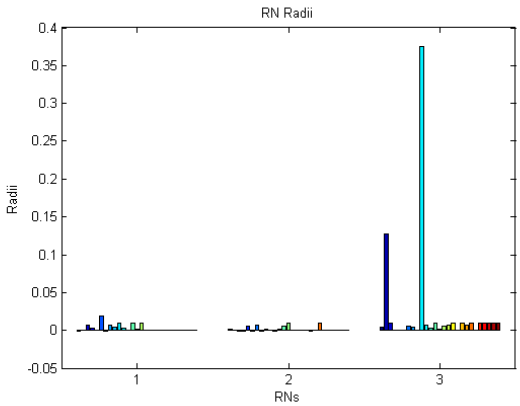
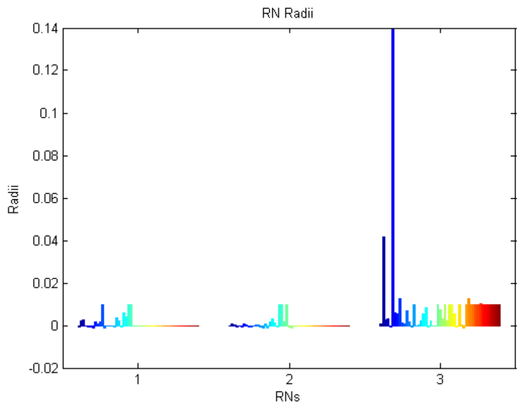
ECF parameters: Max Field = 1, Min Filed = 0.01; Number of nodes which are referenced to determine the class of the current sample MofN = 3; Number of Membership Functions (MF) = 2.

Contrary to the results obtained (Table VII-8), it was expected that for a computationally slower, off-line mode there would be higher classification accuracy with possibly fewer generated rule nodes than in the faster one-pass algorithm alternative. Although these observations with maximising classification accuracy would warrant further investigation they were considered outside of the primary scope of this study.

ECF Classification and Rule Reduction

ECF rules and their reduction strategy by using alternative, reduced dimension data sets (see Table VII-9 and Table VII-10) were investigated. To address the relatively high classification results with one epoch parameter, an ECF with the same settings was investigated further applying computationally more expensive cross validation.

Table VII-9. ECF rules reduction on alternative data sets (Table VII-5) classification accuracy for 80-20% holdout.

<table>
<tr><th colspan="2">ECF - Overall accuracy and rule nodes visualisation</th></tr>
<tr><td>Data Set 2
Golf data set variable #5
Overall accuracy = 84%
No. of rule nodes = 63 (single input variable)</td><td>Data Set 3
Golf data set variable #2
Overall accuracy = 74%
No. of rule nodes = 101 (single input variable)</td></tr>
<tr><td>
</td><td>
</td></tr>
<tr><td>
</td><td>
</td></tr>
<tr><th colspan="2">Comparison</th></tr>
<tr><td>Better overall classification.
Smaller number of rules.</td><td>Less accurate classification.
Larger number of rules.
Considerable decrease in class 1 accuracy.
Minor decrease in class 3 accuracy.</td></tr>
</table>

As expected, a data set containing the highest ranked variable 5 (see SNR ranking, Figure VII-9), produced relatively good overall classification accuracy (84%) when compared to data set #1 (Table VII-8) containing all the variables (90%).

A view in this thesis is that machine-generated rules should be close to arbitrary number 7 (as the number of random items we may hold in working/short-term memory). Another view is that a coach and learner will associate items with an output class e.g. what constitutes a 'good' swing, rather than considering all variations of critical features associated with e.g. 'good' and 'bad' swings. For this reason the equations (VII-1) take into account input space reduction and ignore the output class dimensionality.

Table VII-10. Summary of Rule Number (RN) and input space dimensionality reduction resulting from classification results.

	No. of rule nodes	No. of variables	Dimension
Data Set 1, All golf data set variables:	69	6	414
Data Set 2, Golf data set variable #5:	63	1	63
Difference:	6	5	

Calculation from the Table VII-10:

Reduction Ratio = 0.15
Reduction = 85 [%].

Where:
Dimension = (Number of Rule Nodes) x (Number of Variables)
Reduction Ratio = (Reduced Dimension) / (Original Dimension) (VII-1)
Reduction = (1 – (Reduction Ratio)) x 100 [%].

Machine rule reduction *and their presentation to humans* are considered a separate research topic not central to the thesis, but important for future bridging of CI, kinesiology and other related areas.

Cross-validation of ECF Classification of the Golf Data Set

To investigate the ECF classification with the same parameters further, the more computationally demanding *k-fold* cross-validation approach was used. Table VII-11 compares two cross-validation folds. Both cross-validations resulted in slightly less than 90% overall accuracy. Compared to the 80-20% split *holdout*, the results from 5-fold cross-validation are the nearest equivalents in proportional *k-fold* data split. The 10-fold cross-validations have shown the increased *Class Performance Variance*.

Table VII-11. 10-fold and 5-fold cross-validation results for ECF classification of the golf data set (text report produced in NeuCom ver. 9.19 Student Ed.).

5-fold cross-validation	**10-fold cross-validation**
=== Parameters settings === Maximum Influence Field : 1 Minimum Influence Field : 0.01 M of N : 3 Number of Membership Functions : 2 Number of Epochs : 1	=== Parameters settings === Maximum Influence Field : 1 Minimum Influence Field : 0.01 M of N : 3 Number of Membership Functions : 2 Number of Epochs : 1
=== Overall accuracy for each fold === Fold 1/5 : 93.46 % Fold 2/5 : 87.74 % Fold 3/5 : 90.57 % Fold 4/5 : 87.74 % Fold 5/5 : 87.74 %	=== Overall accuracy for each fold === **Fold 1/10 : 98.15 %** Fold 2/10 : 86.79 % Fold 3/10 : 90.57 % Fold 4/10 : 88.68 % Fold 5/10 : 90.57 % Fold 6/10 : 83.02 % Fold 7/10 : 83.02 % Fold 8/10 : 86.79 % **Fold 9/10 : 83.02 %** Fold 10/10 : 88.68 %
=== Summary confusion table === **23** 11 1 6 **10** 2 12 24 **442**	=== Summary confusion table === **22** 10 2 11 **8** 6 8 27 **437**
=== Summary Overall Accuracy === **89.45 +/- 2.56 %**	=== Summary Overall Accuracy === 87.93 +/- 4.65 %
=== Summary accuracy per class === Class 1 : 56.10 % Class 2 : 22.22 % Class 3 : 99.33 % Class Performance Variance : 0.65	=== Summary accuracy per class === Class 1 : 53.66 % Class 2 : 17.78 % Class 3 : 98.20 % Class Performance Variance : 0.71

This observation of classification variance on a mid-sized unbalanced set (Table VII-12) led to the conclusion that similar cross-validation phenomena may occur as the incidents with small data sets introduced and investigated in Chapter 4. The incidents in the case of golf data would be defined as probability for increased distribution variance in test/train portions for a classifier that shows different classification accuracy for each individual class. With the unbalanced proportion of test data compared to training data there is an increased probability for accidents influencing class performance variance.

Table VII-12. ECF classification results, confusion matrix showing included class presence in test portions for saved data for 10-fold cross-validation and comment linked to probability event *P(C)*.

Fold #	**Overall Accuracy (OA)**	**Confusion Table (CT)**	**Class 1 samples**	**Class 2 samples**	**Class 3 samples**	**Comment linking: *P(C)* , OA and CT**
1/10	**98%**	**4** 0 0 0 **1** 0 1 0 **48**	5	1	48	The highest proportion of class 3. Non-proportional class distribution resulting in high OA.
2/10	87%	**5** 3 0 2 **1** 0 0 2 **40**	7	6	40	
3/10	**91%**	**1** 1 0 1 **0** 0 1 2 **47**	3	3	47	All class 2 samples misclassified. Majority class = 100% accuracy.
4/10	89%	**2** 1 0 1 **0** 1 0 3 **45**	3	4	46	
5/10	91%	**3** 0 0 0 **0** 0 1 4 **45**	4	4	45	
6/10	**83%**	**1** 1 2 2 **3** 1 1 2 **40**	4	6	43	High presence of minority classes.
7/10	**83%**	**1** 2 0 1 **1** 2 0 4 **42**	2	7	44	High presence of class 2.
8/10	87%	**0** 1 0 1 **0** 1 2 2 **46**	3	3	46	
9/10	**83%**	**3** 1 0 1 **1** 1 1 5 **40**	5	7	41	High presence of minority classes in testing portion (excluded from training portion).
10/10	89%	**2** 0 0 2 **1** 0 1 3 **44**	5	4	44	

Note: Unlike in Experiment 1 (Chapter 6), where classification results were larger than 99% but smaller than 100%, the Overall Accuracy (OA) here is rounded to nearest integer.

To validate the above mentioned assertions for an ECF classifier (Table VII-11), the highest and the lowest achieved classification accuracy and their test/train distributions should be investigated:

1) More minority data difficult to classify in the testing portion – higher than average overall accuracy (**Fold 1/10 : 98.15%**).

2) Less minority data difficult to classify in the testing portion – lower than average overall accuracy (**Fold 9/10 : 83.02%**).

Table VII-12 includes comments and observations for selected folds of saved data from 10-fold cross-validation from Table VII-11. This is inline with the novel formula for validation incidents probability *P(C)*, (IV-1) (introduced in the Chapter 4) and are an example of 'parallel' minority class probability distribution of *k* samples to be selected for testing portion (Figure VII-7).

Reflection Points

The analysis of data collected from the subjects, predominantly novices, reveals that the most common (majority class) swing tendency is to produce 'outside-in' ball incidence that may result in a tendency to slice rather than produce a straight shot (see Figure VII-4).

> ***During the time you are practicing and training it's 80% physical and 20% mental, but for some reason, when it comes time and the gun goes off it's just the opposite: it's 80% mental and only 20% physical.***

Mark Spitz, Olympic gold medallist,
(Pos: [7:10 - 7:25], www.youtube.com/watch?v=ed231uG81BI, accessed 16 Oct. 2012).

For learners passing beyond an initial learning programme enabling them to establish a routine with a desirably 'correct' technique, a possible assumption regarding tendency to slice may be related to the impact zone and ball addressing. For example, when addressing the ball with an iron club, the 'feel' for the impact zone and wrist motion could be described as 'a bit early', while for a driver it could be 'a bit late'. By experimenting with a single variation of a swing parameter to an established routine of swing technique (together with combining practice to regaining technique and rhythm), a player may hypothetically accelerate learning and adaptation control of the ball flight and help to develop coping strategies to correct the swing at the competitive stage.

For coaches, integrating an emphasised focus on the impact zone and variations of swing parameters may inspire new coaching scenarios/practice drills. For coaches in other disciplines, the high-level property of this case study could be transferred to coaching tennis serving, for example.

For golf manufacturers the finding indicates a potential to design golf drivers optimised to compensate for targeted customer group skill level (club head, impact 'gear effect', weight distribution, shaft flex, club face properties and others).

For kinesiology and biomechanics research the above reflection may inspire new research directions to inform coaching, bridging cross-disciplines and sport equipment manufacturing.

5. Chapter Conclusion

In this case study, the 'swing plane' heuristic predicting a ball flight category has been validated using data collected from multiple subjects with successful implementation using ML/connectionist models and supervised learning based on objective measures (see Chapter 4 and Figure IV-9). While achieving relatively good classification results (approximately 90%), machine generated rules that govern the inference are considered too numerous and too complex for human comprehension at present.

The cross-validation analyses have shown a presence of randomly selected test samples that are not representative of the available unbalanced data set resulting in variations of overall accuracy, demonstrating the need for prior data analysis (e.g. Figure VII-7) and novel validation incident estimation formula (IV-1).

As a result of analysis of the swing plane variables (Table VII-3 and Table VII-4), the impact zone segment (or variable 5, the last downswing segment) has the highest discriminative prediction property related to swing error, while the backswing towards the top of the swing has the lowest. This finding is consistent with Figure IV-1 and Table VI-1, Experiment 1.

Chapter 8

VIII. CONCLUSIONS, CRITIQUE AND FUTURE DIRECTIONS

Not everything that can be counted counts, and not everything that counts can be counted.

Albert Einstein

As introduced, this thesis represents a programme of work that "set out to understand, model and automate aspects of augmented coaching. Inherent to coaching is the qualitative assessment of human motion, which requires consideration of a set of challenging, largely subjective 'hard-to-quantify' *heuristic* elements" (p. 25). The demonstrated application of candidate connectionist methods for the purpose of achieving automated motion assessment equivalent to that performed by a coach provides evidence that human motion can indeed be assessed by a machine. Although only the critical components of *augmented coaching systems* were addressed in this thesis, through a series of development-experiment cycles, novel outcomes were achieved by applying candidate connectionist approaches via newly constructed software components[28]. The novel outcomes started with the demonstration of automated assessments of previously unseen tennis swings achieved on a relatively small data set and concluded with a golf case study addressing swing accuracy or a relatively large and unbalanced data set.

[28] Disambiguation note: The software components referred in this thesis were 'building blocks' or critical components of ACS design, rather than the object oriented design components, packages, or Web services.

1. Summary of Achievements

The aim of this thesis was to advance sport science and to automate aspects of qualitative analysis required to assess human motion in sporting activities. The novel design approach adopted incorporates the ability to model and automate a coach's implicit knowledge.

The automation of augmented coaching achieved through this research was based on the use of connectionist methods. Automated qualitative assessment encompassing movement error detection similar to that a coach would perform provides capabilities equivalent to: (1) Holistic subjective assessment (mapping to 'top-down' view); and (2) Predefined subjective adherence to coaching rules or heuristics (reflecting a 'bottom-up' view).

An approach to movement evaluation that is both subjective and flexible was demonstrated via supervised learning and weighted assessment orchestration. This approach supports the personalisation of automated assessment for a targeted skill level and specific goals associated with coaching scenarios.

The experiments linked to the extraction of machine rules indicated: (1) The possibility of additional support personalisation by combining evolving and incremental learning with extraction and insertion of previously extracted machine rules; and (2) That the number of extracted rules, for the scenarios considered in this thesis at least, may be too complex to directly inform the coaching process.

By combining weighted sub-space modelling mapped to individual coaching rules it was demonstrated that: (1) The output from the learning system can be used for feedback as a 'bottom-up' diagnostic assessment; (2) The assessment system can provide meaningful explanations to humans (as *diagnostic outputs*); and (3) It is possible to achieve assessment automation utilising relatively small data sets.

Experiments in sub-space modelling utilised feature extraction techniques that produced low feature space dimensionality relative to the available data. This was possible because the selected coaching rules in the experiments represented relatively isolated 'bottom-up' assessment elements (as a sub-set of the problem space). Mapping of coaching rules to assessment elements could be included in qualitative analysis (e.g. *systematic observation strategy*) and then included in the developed framework, in diverse sports. The ACS framework, architecture, models, algorithms and visualisation are considered to be flexible and reusable in terms of mapping of the assessment elements that are relevant to diverse sport disciplines and related contexts.

Of value in coaching and in kinesiology, the production of replays with visualisation of *diagnostic outputs* is laborious and time consuming. In this context, novel automation outcomes were achieved by combining ICT infrastructure technologies; the qualitative analysis of human motion, using systematic approaches derived from kinesiology, coaching and biomechanics; and connectionist and evolving methods. The contributions that follow represent multiple outcomes in terms of research and practice (see also additional detail, Appendix A).

Note that novel contributions to a number of areas have a degree of overlap because of the cross-disciplinary nature of this work. The same is true for novel contributions regarding applications that utilise specific existing technologies in new discipline areas.

1.1 Contributions to Augmented Coaching Systems

Contributions to ACS and delivering a synthetic coaching user-experience are based on:

Automated assessment of motion data which incorporates qualitative and quantitative analysis approaches. Unlike traditional algorithmic approaches, the prototype functionality supports: (1) Supervised learning as captured expert assessment decisions and as measured knowledge of results (KR); (2) Assessment of previously unseen motion data with adaptation of internal machine knowledge through the use of ECOS; (3) Human-intelligible motion analysis automation, which was achieved as descriptive error detection linked to coaching rule diagnostics (i.e. MoHEM/CREM operation); and (4) Personalisation via flexible (i.e. user-configurable) and subjective assessment criteria. In addition, personalisation is supported via machine learning (ML) rules extraction and insertion i.e. ECOS can store and recall ML knowledge by extracting/inserting rules as subjective criteria or as snapshots in life-long learning. In a hypothetical example, if as a result of injury a learner is required to undergo a rehabilitation program with different assessment criteria until fully recovered, it would be possible to re-initialise the machine knowledge to the assessment capability at an appropriate point in time before the injury had occurred and to continue evolving the machine learning system's operation.

Layered architecture for augmented coaching systems. The layered software design approach delivered here enables various components from this thesis to be developed and tested in isolation and incrementally added to a system for external validation for a given sport or other context. The novel prototype utilises an evolving, extensible, replaceable, multi-tiered architecture that supports: (1) Communication between the modules, enabling synchronisation of motion data viewing and machine feature processing; and (2) Separation of each sport's domain-specific user interface from the processing and replay capabilities (as *external synchronisation for visualisation and replay*).

The generic design intention of the prototype includes: (1) User-profile oriented tasks such as self-coaching/learning, qualitative analysis and supervised machine learning; and (2) The potential for modification to suit other sports with similar assessment requirements to golf and tennis. Such systematic technology transfer also supports application to and integration with embedded, mobile, pervasive systems to virtual reality (VR) for ACS environment applications (e.g. Lee et al., 2012; Lefkow, 2012).

Framework related to ACS and modular MoHEM/CREM design, which includes critical feature design optimisation taking into account the constraints associated with the operating environment, contexts and motion capture. The MoHEM/CREM modular assessment in the form of diagnostics provides a means of capturing and providing human-comprehensible feedback and assessment validation criteria. By considering the motion capture constraints the approach also supports the design of a set of feasible MoHEM/CREM modules that (will) work with a variety of I/O devices e.g. low cost motion capture systems (e.g. Microsoft's Kinect).

Enabling automated, diagnostic-based intervention-feedback suitable for future analyses, based on connectionist approaches, large motion data sets, feedback optimisation and the matching of interventions to diverse goals.

Media Player Abstraction Layer, for qualitative analysis and (re)viewing human motion.

For novel *external synchronisation for visualisation and replay* functionality, two diverse media visualisations of motion data were designed and used in both case studies. The first viewer for 3D motion data was an animated stick figure player that supported interactive viewing from any angle. The second viewer was a 2D media player equivalent (developed to facilitate feedback to subjects in the golf case study from captured DV video format). The functional design for both viewers including *external synchronisation for visualisation and replay* was optimised for the task of qualitative video analysis.

Some of the resulting achievements were: smooth concurrent multi-video replays of pre-defined sub-sections of video and incremental frame step navigation. *External synchronisation for visualisation and replay* is shown in integration with: user interface and modelling environments such as MATLAB® (Chapter 5 and Appendix B).

1.2 Contributions to Bridging Disciplines

Cross-discipline contributions include:

Combining qualitative and quantitative approaches such as modelling techniques derived from qualitative human motion analysis, biomechanics and connectionist methods. Similar to the identification of key elements and critical features considered in biomechanics, the determination of dynamic and static machine features obtained from motion data was derived from multi-level temporal and spatial transformations. Novel concepts associated with *human motion modelling and analysis* (HMMA) and machine features that bridge disciplines include: personalisation, orchestration/sub-space modelling, coaching rules, coaching scenarios and skill level.

A framework for ACS design, feature selection and feature extraction techniques applied to HMMA – inherent to the connectionist approaches used here – which can be influenced by strategic design and the data processing concerns for the machine learning system. For example, the feature extraction algorithms can be optimised for the purpose of specific operational requirements and trade-offs (e.g. processing speed, feature space dimensionality and motion capture prerequisite requirements).

Introducing and addressing the principle of similarity grouping and associated decision boundaries. This was investigated in terms of: (1) Predicting the random nature of training/validation incidents; (2) Output class distribution; (3) Analysis in relation to observed groups, internalised data profiles (e.g. swing type) and individual classes; and (4) Enabling *external synchronisation for visualisation and replay* capability, linking subjective (expert) grouping of motion data samples with numeric machine data.

External synchronisation for visualisation and replay functionality was integrated in processing layers: communication, presentation and interaction logic. This functionality provided interactive replays and modelling tasks associated with motion data and (cross-discipline specific) software integration. Adding *external synchronisation for visualisation and replay* capability to existing modelling environments enhances their existing functionality (e.g. replay control capability linked to ML data) as well as enabling rapid modular prototyping based on qualitative and quantitative modelling tasks associated with motion data.

1.3 Contributions to Coaching

In detail, the contributions include the following:

Qualitative assessment automation based on flexible, subjective and objective criteria was enabled by allowing the user to adjust assessment skill levels and to select appropriate CR and by the machine capability of *supervised learning*. Machine-based *supervised learning* was used to capture expert's knowledge in the form of coaches' observations to be transferred into an initial system before its autonomous operation on future data. If needed, measured outcomes can also be utilised for *supervised learning*, as assessment automation based on objective criteria.

A selection of coaching concepts, principles and rules associated with diagnostics of human motion with criteria related to skill level and strategic/personalised training levels which are transferable to a machine. These were enabled by the evolving and incremental modular system architecture design and user interface that may reflect human thinking. The incorporated two-way communication visualisation/replay tool (as *external synchronisation for visualisation and replay*) supports motion data in 3D data format.

Interpretation of knowledge discovery focused on prioritised impact/action phase and its integration into movement. The knowledge discovered from the demonstrated methods of data analysis and modelling interpretation suggest that priority should be given to specific movement phases that contribute the most to the outcome(s) of the movements. For coaches, that implies specific coaching activities focused on or 'around' prioritised movement phases and their integration into coaching of a whole movement (see Appendix A). Inferring this finding to coaching/practicing of the segment around the impact, throw or kick, the expected benefits are: learner's gaining a 'feel' for the action zone, and increased ability to modify the movement techniques (if needed) in earlier segments, to correct or add controlled variations to standard movement or to adapt to a new technique.

Contributions to tennis coaching. Chapter 6 includes the following interpretative findings[29] in this *problem space* context, based on motion data analysis of 43 swings and connectionist modelling:

- **Attention to occluded parts of a player's pelvis.** The algorithm and model associated with the 'swing width' heuristic/coaching rule and injury prevention

[29] Related to the available data set – representing captured context in data – that may be in line with a coach's personal experience and expertise.

showed higher accuracy in comparison to a human expert when taking into account occluded parts of a player's pelvis;

- **'Low to high' swing rule** data analysis showed that it appears easier to achieve 'low to high' swing action with a forehand than with a single-hand backhand; and
- **'Swing width' performance versus safety** – the forehand is likely to be executed with more focus on performance (showing variation of swing width), while the backhand swing seemed to be executed with a tendency to safety or injury prevention for the novice to intermediate skill level player.

Contributions to golf coaching. Chapter 7 includes the following findings based on 531 recorded golf swings from 14 golfers:

- **Natural learning tendency to produce swings with 'outside-in' incidence error**. Most learners will produce a golf swing with an 'outside-in' incidence error. A coach may advise if needed; e.g. use of a complementary driver club with a property to compensate for consistent slicing during the learning progress from beginner to intermediate or until a player learns to improve control of the ball flight trajectory;
- **Swing plane impact zone segment** has the highest discriminative prediction property related to swing error while the backswing towards the top of the swing has the lowest. This finding was based on the analysis of measured and reported errors as variations from linear swing plane segments by the SmartSwing club system; and
- Based on **visualisation of the swing plane** and the SmartSwing assessment model, the discriminative prediction ranking indicated that the 'ideal' golf 'swing plane' boundaries may not be linear (v-shaped) but instead, may be visualised more as a 'y-shaped funnel'. For coaches, interpreting this machine knowledge discovery based on the captured data would suggest for the resulting ball flight that the 'feel' and movement around the impact are more important than focusing on correcting individual swing variations that are perhaps more noticeable e.g. around the last backswing segment. In the context of HMMA (Chapters 2 and 3) and developing a learner's *kinesthetic proprioception*, this would not apply to novices but to more advanced skill level profiles.

The user's coaching experience for learners in this thesis was linked to ACS capabilities of replay and intelligible automated movement diagnosis, which can lead to fully developed instruction and intervention feedback. Other supporting concepts from this thesis include:

skill acquisition, *kinesthetic proprioception*, awareness of the 'feel' around the impact, 'learning-by-doing' and personalisation.

1.4 Contributions to Kinesiology

The main contributions to kinesiology are in: (1) Bridging disciplines and contexts linked to automation aspects of qualitative analysis of human motion; (2) Human-intelligible diagnostics, based on subjective and flexible assessment criteria; and (3) Advancing the state of augmented coaching systems and sports performance technology. Examples include:

The novel application of computational intelligence in sports and related discipline areas. As demonstrated in this thesis, since 2003, novel CI/connectionist approaches can provide machine-equivalent capabilities to human qualitative motion analysis/assessment. The ideas and concepts presented as a foundation for this work are generally applicable to multiple sports disciplines and related areas. In these contexts, the new application of CI/connectionist systems demonstrates a system design that can assess human motion based on subjective human (expert) and/or objective measurement assessment criteria. After being trained on initial examples by an expert, a system can continue its autonomous operation on previously unseen data. With the application of the evolving paradigm, such systems can evolve and adapt their operation in an incremental life-long learning fashion. The novel concepts and framework include interlinked strategic aspects of: (1) Data processing and feature transformation; (2) The prerequisite of data capture constraints; (3) Incremental/evolving architecture; and (4) Aspects covering modelling, coaching and user learning contexts.

The added value of cross-discipline research. Utilisation of CI disciplines such as knowledge engineering enables, supports or provides insights based on data and algorithms that have the potential to improve and extend related disciplines including coaching practice.

Aligning existing qualitative analysis models with CI-based approaches, incorporating temporal and spatial analysis for machine feature extraction and transformation. This includes the notion of dynamic and static CR. Machine features obtained via the experiments may be identical to measured critical features in biomechanics analysis or ML-alternative high-dimensional spaces, incomprehensible to the human mind.

Impact/action zone temporal segment computation is indicated as the most suitable machine equivalent global assessment model, based on similar findings from both case studies (tennis and golf). The discriminative properties of swing plane segments in golf are in line with cross-discipline findings related to the discriminative properties of the impact zone in tennis, which was used in the global assessment model to categorise tennis swings. Although these initial findings and concepts are promising, it would be beneficial to confirm and validate these outcomes as general principles by conducting further complementary studies and by involving more athletes performing characteristic movement patterns in a variety of styles.

1.5 Contributions to Computational Intelligence

The main contributions to CI include the following:

Extending CI to new application areas and disciplines related to human motion in sporting activities. From identified gaps (Chapter 1), this will enable further advancements in sport science, augmented coaching and sport performance technology, and related areas.

Experimental evidence supporting the application of connectionist and other CI approaches to automated analysis of previously unseen motion data in a manner similar to qualitative analysis conducted by an expert. Novel contributions include:

- **New contexts of sport and human motion modelling**. The supporting examples include: automated aspects of human motion analysis, implementation of heuristics and coaching rules into a machine, combining critical features in biomechanics with temporal and spatial *machine learning* approaches; and
- **Impact/action zone automated assessment model**. As indicated in the experiments, the global assessment model around the impact/action zone was found to be the best candidate for machine assessment across more than one sport discipline (requiring relatively high-levels of data acquisition precision and sampling rates).

Taxonomy of the research fields and contexts linked to data analysis and human motion modelling and analysis (HMMA). This includes: expected scope of CI modelling tasks and related data quantities; identified computational data processing and automation contexts; and the notion of task separation into independent software components to achieve a modular architecture for augmented coaching systems (ACS) applicable to a diverse range of sports and related disciplines.

Framework for ACS and HMMA, relying on CI approaches.

Two-way communication for visualisation replay and qualitative analysis as a modelling tool for supervised learning (*external synchronisation for visualisation and replay*) enabling linking of a motion data sequence in 3D or 2D video format with a representative *machine learning* sample. In this thesis *machine learning* samples or features were identified as being potentially high-dimensional or incomprehensible to the human mind.

Novel probabilistic formula supporting modelling of human motion activities applied to predicting *k*-samples from a 'sub-group' to be randomly selected for training/learning/validation. A 'sub-group' may be based on an expert's similarity grouping perception, ML, statistical or distance-based clustering or output class distribution of a captured activity. The novel formula is linked to issues such as: predicting the cluster or output class selection into test/training portion; cross-validation fold size estimation; discrepancy in cross-validation results on unbalanced data due to random data selection (see Chapter 7, cross-validation classification results). The distribution analysis of *k*-samples as independent variable was found to produce a shaped curve similar to Gaussian bell (Figure VII-7). The formula validation using simulation with large numbers and *holdout* cross validation was reported in (Bačić, 2006b; Bacic, 2008b).

1.6 Contributions to Information Science and ICT Infrastructures

Prior to this thesis and summarised in the literature review, there were no solutions to automating aspects of qualitative analysis of captured human motion, a critical element in enabling an automated coaching experience based on captured motion data. Contributions to information science and ICT infrastructures include the following:

The novel application of connectionist systems in sports and related discipline areas.

Addressing the gap in automating the coaching cycle (preparation; observation/data capture; analysis – evaluation/diagnostic; and feedback/intervention) **by automating the analysis – evaluation/diagnostic stage**. Existing approaches related to sport performance technologies involve direct computation through the application of traditional algorithmic and analytical approaches. Automated aspects of qualitative analysis delivered here are similar to the actions of a coach, who observes, diagnoses and provides an appropriate level of feedback.

Augmented coaching systems for providing end-user coaching experience based on CI incorporate an automated diagnostics assessment capability with a focus on swappable and extensible components.

2. Implications, Limitations and Critique

The motivation for this subsection is to reach a broader audience from a range of disciplines by linking the contributions with consideration of the thesis' implications, limitations and critique, from different perspectives e.g. the technologist, researcher and practitioner communities.

2.1 Implications Specific to Coaching and Biomechanics

The introduction of automated qualitative assessment in augmented coaching and sport performance systems is not promoted here as a technological substitute for the role of a coach or of human intuition, but rather as a new dimension in coaching and learning. If a machine-learning based augmented coaching system is trained using inconsistent coaching assessments, then the augmented coaching system will not deliver automated assessment to its full potential. Ultimately, the machine learning system, that may well produce automated diagnostic outputs as feedback, is not viewed as a substitute for an expert coach's judgment or thinking.

In terms of enhancing the human experience, it is plausible that augmented coaching and promoting human movement (e.g. via 'learning-by-doing', digital entertainment or augmented coaching environments) should improve health, longevity and quality of life, and for some learners it may accelerate the journey from beginner to expert.

It is contended, in this thesis, that the following implications are relevant and of value:

Shifting low-level cognitive coaching tasks to machine-equivalent automated tasks, enabling a coach to focus on higher-level tasks. For example, if a player's motion data is available, the components developed for this thesis can be modified to provide instant assessment statistics regarding the player to an end-user. For a coach observing his/her student(s), mental focus can be shifted from attention to low-level diagnostics to a more holistic Gestalt-type observation and perceptual consideration, including game patterns, vision for the game and identifying goals that can then be followed up with individuals and/or compatible groups in appropriate coaching scenarios (e.g. interventions and drills with associated assessment criteria). It is also expected that a coach's cognitive response may be quicker or less prone to bias if a part of the diagnostic process is offloaded to a machine.

Opening new perspectives and opportunities for the use of coaching insights (including related coaching scenario activities) in facilitating *supervised learning* and the consequent design of augmented coaching systems, video games and digital entertainment environments associated with motion and motion capture systems. In addition to having access to facilitate the optimal operation of MoHEM/CREM-based qualitative diagnostics assessment, a coach will be able to apply *coaching scenarios*, provide feedback and conduct more strategic assessment of play/competitive situations, for opponent and trainee, based on acquired motion data.

The customised ability of a learning system to assess motion could be captured as the intellectual property of a coach or biomechanist or as his/her contribution to systems design. A given coach's subjective assessment criteria on observed motion data transferred into a machine may produce better classifications or prediction results than if the same learning system was trained by other coaches. The same is true for feature selection and feature transformation. As such, assessment data associated with observed motion represents a coach's (or a design team's) tangible intellectual property linked to modelling, classification and system assessment accuracy. Chapter 6 included a demonstration of the same algorithm resulting in better classification when taking into account occluded parts of the pelvis associated with the 'swing width' coaching rule (tennis case study). Together with the assessment, a coach's role can be extended in terms of becoming a member of an augmented coaching system design team or in an equivalent design role in the development of game or digital entertainment systems.

Specifically, a biomechanist in an augmented coaching system design team may contribute to the associated *systematic observational strategy*, data acquisition rigour, critical feature insights and their transformation to machine features, as well as validation aspects during design stages.

Examples of *knowledge discovery* from motion data. As shown in the examples of the 'swing width' coaching rule, and in relation to the 'swing plane' in the golf case study, *knowledge discovery* findings can be obtained as a result of utilising methods from the *knowledge* *engineering* discipline, leveraging *machine learning* or associated modelling or data analysis to advance the state of the art of coaching. It is contended in this thesis that the prospect of *knowledge discovery* contributing to kinesiology would be increased with the conduct of further cross-discipline research similar to this and by broadening the research community.

2.2 Implications for Analysis of Human Motion

Hybrid, multimodal motion data acquisition. Where video cannot produce satisfactory motion data sampling accuracy and resolution, the augmented coaching system can be integrated with additional motion acquisition hardware (e.g. embedded electronics) achieving a trade-off of higher accuracy, sampling and real-time performance with lower obtrusiveness as dictated by the scope of the project (see Chapter 4). Future systems are expected to combine video information with real time animation and overlay data relevant to learning.

Lowering the cost/functionality ratio of available video analysis software. Utilising a viewer that can be integrated with various software environments for a coach may lead to commercial alternative low-cost solutions for video presentation and analysis. For research in CI, this represents an opportunity to create 'building blocks' and disseminate software that can automatically recognise video or 3D motion data events and be integrated with diverse ICT infrastructures.

Reusable libraries and utilities for human motion data modelling. Experimenting with 3D viewer animation performance relying on a single-core CPU allows multiple replays without freezing frames or frame drops, with smooth interaction, as required for qualitative analysis. Future work is likely to include 3D, virtual reality and immersive reality viewing/replay capabilities merging data, animated surroundings and video. The *external synchronisation for visualisation and replay* usability and functionality specific to qualitative analysis and CI modelling are likely to be extended to internet video viewing content providers (e.g. YouTube interfacing controls and libraries, and video trans-coding where needed for video coaching purposes).

2.3 Limitations and Critique

The following limitations are acknowledged, many of them representing avenues for future research and development:

The need for further work to confirm and extend achieved results based on additional data sets from diverse sports and athletes, to provide prospective evidence of efficacy in helping individuals to improve their movements.

The coverage of the case studies. The purpose of having two case studies is to demonstrate the ACS framework with various critical CI components providing novel contributions that are applicable to more than one sport discipline, rather than giving deeper consideration to a single software application specialised for one domain. In doing so, the case studies complemented one another's limitations as shown in Table VIII-1.

Table VIII-1. Complementary coverage and limitations of the case studies.

Property		Tennis case study	Golf case study
1.	Experiment environment.	Indoor (laboratory).	Outdoor (driving range).
2.	Ball impact.	No.	Yes.
3.	Participating subject(s).	Intra-subject.	Inter-subject
4.	Perceived degree of obtrusiveness.	Moderate. Retro-reflective markers attached to bony landmarks and racquet.	Minimal. Golf club had *'normal look-and-feel'*[30]. Subjects had to press 'Start' button on the club (Figure VII-2).
5.	Rule based concept.	Multiple Coaching Rules/Heuristics.	Single Heuristic of a 'swing plane'.
6.	Assessment criteria.	Subjective.	Objective.
7.	Data set – number of samples relative to problem dimensionality.	Relatively balanced and small to mid-size (43 samples).	Relatively unbalanced and mid-size to large (531 samples).
8.	3D data transparency.	Access to raw ASCII motion data. Temporal and spatial computation (e.g. swing and event recognition).	3D replay and access to computed values from swing motion from SmartSwing software.
9.	Machine learning features.	Temporal and spatial feature extraction techniques.	Feature selection and feature transformation.
10.	Probability of incidents *P(C)* included in analysis.	Internalised expert grouping and swing distribution.	Cluster analysis and output class/label distribution.

[30] Verified by NZPGA affiliated golf-professional.

The two case studies together sufficiently demonstrated the viability and feasibility of the ACS framework, providing more than adequate coverage of the concepts, theoretical foundations and practical aspects related to the scope, aims, and boundaries of the thesis.

Closed-skill activity selected as the initial problem domain. In contrast to golf driving range practise, tennis is recognised as an open-skill sport, but the preliminary experiments were oriented towards closed-skill assessment. Variations in swing execution were differentiated in terms of clusters representing good and bad swing technique.

Extending the existing data set from the tennis case study with an affordable 3D online data acquisition system would be immediately beneficial to further develop an ACS with greater commercial and communal adaptational potential to assist players with a large variety of swing execution styles. The size of the data set used here, captured in a controlled environment by a tennis expert, ensured sufficient data context and coverage required for embedded tennis case studies, ranging from heuristics and CR that were relatively simple to label to those with relatively narrow decision boundaries, requiring the non-trivial development of a novel specialised 3D animation viewer for their accurate and rigorous inspection. The captured context in the 3D motion data set for tennis was also sufficient for demonstration, as acknowledged by the New Zealand coach (Appendix E) who recognised the immediate commercial potential related to the 3D data set and the associated 3D animated stick figure viewer used in the tennis case study (see the supplementary CD).

Adaptive diagnostic outputs as MoHEM/CREM weighting is not a universal assessment solution. A single approach to the weighting of MoHEM/CREM has been experimented with in this thesis. Non-linear weighted combinations or other forms of orchestration (e.g. through an evolving system) could be investigated as possible candidates to be integrated in the modular architecture based on future extended motion data. However, an adaptive architecture based on MoHEM/CREM weighting is considered as a simple machine alternative for more complex topologies or the tree representation of a *deterministic model* (Hay & Reid, 1982; Hay & Reid, 1984). Alternative modular architecture integrations (tree structures, connectionist ensembles) would address the opportunity to investigate contextual relationships between errors, changes, unlearning ('bad habits') and re-learning.

The need to extend the set of MoHEM/CREM. The MoHEM/CREMs considered in the tennis case study represent demonstrable experimental evidence that meets the intent and purpose of this thesis. As such these MoHEM/CREMs represent a subset of those that could be used in a more extended analysis of motion. Future work will necessarily involve the development of additional MoHEM/CREM case studies (addressing, for example, aspects of grip, balance and fluidity of movements).

Prior to the release of this thesis, the state of the art in motion acquisition-driven video games or augmented coaching systems did not deliver similar capabilities in automated coaching. As a result, the case study analysis and results could not be compared or benchmarked against existing technologies.

3. Future Directions

The future directions and building blocks of this work will:

1. Extend and advance the augmented coaching infrastructure supporting the thesis' main contribution – to enable the use of CI to automate aspects of human motion analysis and coaching based on advancements in ICT infrastructures;
2. Broaden its constituent methodology – to consider further applications of novel CI approaches to kinesiology; and
3. Extend and advance into surrounding contexts – to address a wider range of cross-disciplines and applications as well as more effective data acquisition and multi-modal feedback (see Postamble).

3.1 Extending and Advancing Augmented Coaching ICT Infrastructures

Future advancements in ICT infrastructures that would have the greatest effects on ACS improvements are expected in three separate directions:

1) Input – towards a range of motion capture devices with no (or a minimal degree of) obtrusiveness; minimal setup time and effort; and high portability or operational autonomy where required. In order to advance the work reported in this thesis to reach a broader audience, there is a need for low-cost motion data acquisition and data communication devices. For example, several technologies have been introduced in the last year including Microsoft's Kinect, and development tools such as the Dynamic Vision Sensor (asynchronous temporal contrast silicon retina, http://siliconretina.ini.uzh.ch/wiki/index.php, accessed 11 Jan. 2012), the DepthSense™ Camera (with time-of-flight sensing technology) including iisu™ middleware –

(www.softkinetic.com, accessed 19 Nov. 2011); and the low-power *Bluetooth®* 4 (www.bluetooth.com for sports, fitness and health monitoring devices – www.bluetooth.com/Pages/Sports-Fitness-Market.aspx, accessed 19 Nov. 2011).

Future investigations will be aimed at the integration of: (1) Video; (2) Embedded solutions (e.g. using open source Arduino); (3) Sensory networks; (4) Real-time computer vision (e.g. building on early work on Intel's OpenCV and NVIDIA GPUCV (Viney & Green, 2007); and (5) Integration with consumer electronics including game controllers, motion sensing mobile and tablet devices.

2) Processing, platforms and distributed processing. Computational demand associated with existing and future connectionist models, data capture and other processing tasks can be addressed with distributed processing, including the use of embedded systems and parallel computing.

For example, the current prototype's layered approach and program communication with the single instance of a MATLAB server could be extended to multiple processing instances, multiple platforms or other programming languages operating with multi-core CPUs, with CUDA GPUs[31] and scaling up to clusters, grids and cloud computing platforms.

3) Output – visualisation and usability oriented towards unobtrusive feedback and intervention. Further case studies will be used to extend the *external synchronisation for visualisation and replay* capability to new interface metaphors and to test it in a variety of sports disciplines and user scenarios as well as interfaced with diverse tools and platforms. Further studies in human computer interaction will combine augmented coaching and human motion modelling and analysis with: (1) Multi-modal feedback; (2) Augmented reality, interactive/artificial world environments combined with the latest advancements in 3D spatial immersive environments e.g. including volumetric 3D viewing (Blundell, 2011) based on processed motion data in near-real time; and (3) Robotics to provide interaction.

3.2 Advancing CI in Kinesiology

It was demonstrated through the two case studies presented that CI methods and concepts are transferable between sport research domains. Common to the use of connectionist approaches in other disciplines, there is a need for preferably large databases containing a

[31] High-end NVIDA cards with CUDA libraries(http://developer.nvidia.com/cuda-gpus, accessed 28 Sep 2011)

variety of motion events that will enable future work on event extraction algorithms and their validation and automation. For example, future work on an extended tennis case study with more data would support research into the utility of non-linear weighted or other evolving orchestration approaches as well as diverse feedback optimisations to be integrated into the existing modular architecture.

Continuing to extend CI to coaching and kinesiology, future research will also be more focused on augmented coaching synthesis. Future investigations will include:

Advancing multi-time series event extraction. Future advancements are envisaged in applications of modern evolving connectionist approaches such as: (1) The evolving spiking neural network (eSNN) and liquid state machines (Schliebs & Hunt, 2012); (2) Advancing the work on personalised modelling (Hwang, 2009); and (3) Advancing the selection of personalised data neighbourhoods for example, by extending Euclidean distance approaches (Kasabov, 2007b, 2009) with quantified cognitive distance modelling.

Knowledge discovery transfer. Sharing the interdisciplinary vision advocated by others (Knudson & Morrison, 2002, p. 32), early experiments directed towards transferring high-level properties of the golf case study translated to assessment of the tennis serve show encouraging preliminary results.

Capturing the subjective notion of similarity at multiple levels. At a high-level of processing, this refers to extending the preset weights or manual configuration to utilising automated weight adjustment (Cardle, 2003; Bacic & Zhang, 2004). The corresponding algorithms, based on the use of large data sets, may include artificial neural network ensembles, or other structures that use relevance feedback in refining the weights.

At a low-level of processing, the subjective notion of similarity will inform the continuation of iB-fold algorithm (Bacic, 2008b) variation development utilising pre-partitioned randomisation based on supervised learning data. Case studies will include motion data with expert assessment in terms of both output labels and captured subjective similarity; or configurable distance measures for *machine learning* cluster analysis. The expected benefits include an improved learning rate. Similarly, for cases where there is evident similarity in human and machine decision boundaries, this would open up the opportunity for *semi-supervised learning* utilising large data sets for the purpose of minimising interactive activities for expert-based supervised training.

Using external synchronisation for visualisation and replay of video with matching 3D animated models to facilitate feedback. Existing 3D animated models would include avatar rendering in order to produce useful (and possibly real-time) feedback in virtual reality systems and immersive environments.

Motion data and video/3D synthesis integration. Extending the capabilities of the system prototype should support the use of synchronised video and processed motion data in order to provide augmented feedback and visualisation.

High-level educational concepts. In addition to matching skill level and programme level, personalised and group learning including teaching aspects would include fuller consideration of user profiles, learning styles, and individual and group incremental achievement dynamics.

Providing automated augmented feedback. Future research in providing automated augmented feedback optimised for diverse goals, including education, injury prevention, and rehabilitation, will be based on the foundation established through this work drawing on the availability of larger data sets and architectural advances into evolving novel ensembles of CREM/MoHEMs.

POSTAMBLE

In the author's vision, further advancements of CI in modelling human sporting activities and related disciplines are expected to enable:

1. Personalised coaching environments based on various ICT infrastructures and supporting various coaching scenarios and pressure drills;
2. Strategic competitive pattern recognition, feedback and multi-modal intervention; and
3. Regulation and control for prosthetic control mechanisms (Matsuoka, 1997; Burck, Zeher, Armiger, & Beaty, 2009), based on MoHEM and CREM diagnostic approaches.

Based on this thesis, projected future work includes a range of applications in advancing control mechanisms in intelligent prosthetics (Adee, 2009) and exoskeletons (Strickland, 2012) personalisation, movement learning and optimisation to meet diverse goals. Implementing the augmented coaching paradigm into embedded control devices linked to new brain-machine interfaces (Carmena, 2012), will enable control of prosthetic devices in a natural way with a supervised learning paradigm. This concept will exploit the plasticity phenomenon of the brain and enable cognitive activity to be translated into prosthetic device driving signals via such embedded control devices.

Other control applications include work on future coaching environments based on recent advancements in 3D display technology, virtual and immersive environments (Blundell, 2011) combined with robotics. For sport performance technology and augmented learning environments, the further advancements in applications of CI would be aimed at: (1) Modelling opportunities for various sources of synchronous motion data input[32] in related areas of cognitive prosthetics (shortening OODA loop response times, autonomous advising strategy with real-time processing capabilities of game patterns); (2) Automated injury detection as pathomechanics pattern recognition (Fortenbaugh et al., 2009) to skill modification and skill reacquisition in rehabilitation; (3) Umpiring of stylistic executions (e.g. synchronous diving); (4) Digital entertainment and gaming experience based on augmented coaching/learning; and (5) Combining active and passive machine learning paradigms.

[32] Heterogeneous acquisition devices from environments providing synchronous input (e.g. force-plates, electromyography (EMG), electroencephalogram (EEG) and 3D motion capture) data.

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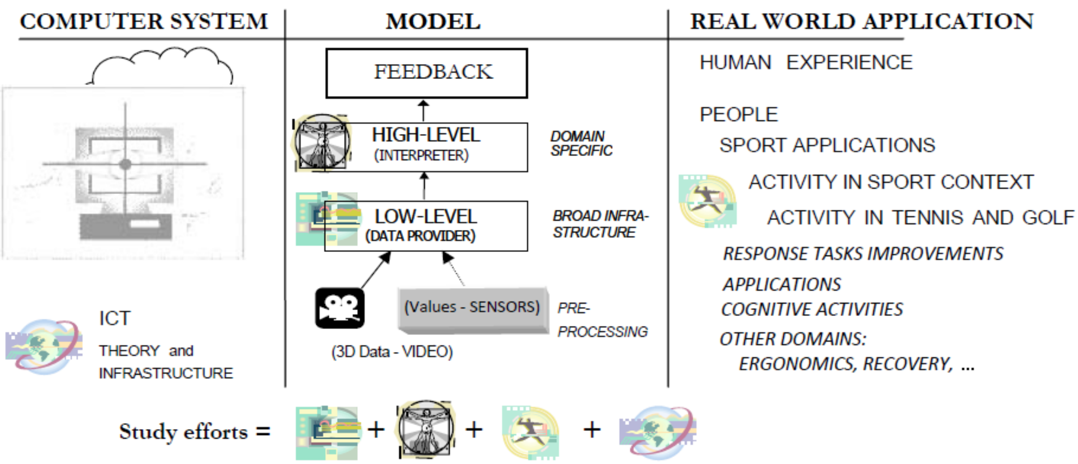
APPENDIX

This section includes in more detail contributions, concepts, mathematical notations, selected source code snippets and additional background information associated with this thesis.
This section also comprises 'loosely referenced', supporting and non-mandatory reading material to reach a wider audience from related disciplines.



Holistic research efforts linked to contributions in augmented coaching.

The figure above depicts the thesis as mixed study efforts, designed with consideration to be transferable to present and future parallel and distributed processing platforms to achieve real-time processing needed for diverse real world applications.

Appendix A: Achievements Summary

Specific discipline and contributions abbreviations (see the table below):

All	… all cross-disciplines included in the thesis
ACS	… augmented coaching systems
C	… coaching
CI	… computational intelligence including knowledge engineering, connectionist approaches (general) and pattern recognition (specific)
G	… gaming and digital entertainment production
ICT	… information and communication technology infrastructures
K	… kinesiology (general) and biomechanics specific discipline aspects
KD	… knowledge discovery context
KE	… knowledge engineering
SE	… software engineering
SM	… sport equipment manufacturing.

Summary of achieved novel synthesis as cross-discipline contributions.

Contribution		Description, relevance and significance	Specific discipline
1	**CI in Kinesiology**	**Novel ability to model and automate coach's implicit knowledge into a machine**.	
1.1	Application of connectionist approaches to augmented coaching systems.	Cross-discipline theoretical foundations required for data analysis and modelling of human motion in sporting and related activities. Automation of aspects from augmented coaching including qualitative assessment of performance and error diagnostics. Demonstrated automated aspects of qualitative analysis of (human) motion data include: evolving assessment, flexible and subjective assessment criteria, movement error diagnostics and personalisation.	ACS, CI, K
1.2	Flexible generic modular extendible and evolving architecture allowing integrative and subspace modelling.	Generic architecture supporting augmented coaching and evolving functional growth. Extensible MoHEM/CREM modular architecture supporting motion data problem-sub-space assessment. Demonstrated automated assessment is similar to human qualitative/descriptive error diagnostics of an observed and recognised motion event (a tennis swing).	ACS, CI, K, G, ICT

Contribution		Description, relevance and significance	Specific discipline
1.3	Providing human intuitive feedback of the observed movement associated with goal of movement, based on flexible and subjective criteria.	For the purpose of providing human intuitive feedback, qualitative assessment of human motion is modelled as diagnostics – using ML implementation of heuristics and coaching rules. Demonstrated problem segmentation is shown in applying a sub-space modelling and ML implementation mapped to concepts of heuristics and coaching rules. In addition, demonstrated holistic motion modelling approach shows that a motion segment can be autonomously assessed e.g. as ('good','bad') swing.	ACS, CI, K, G, ICT
1.4	Personalisation of automated assessment by using ECOS that can extract/insert rules.	Novel personalisation assessment approach is based on combining ECOS and flexible, subjective criteria. Demonstrated: (1) evolving ML principles; (2) utilisation of extracted rules – that can be stored externally (e.g. in a database or a text file) as ML knowledge snapshots; and (3) supervised learning paradigm.	ACS, CI, K, G, ICT
2	**ACS framework, applicable to augmented coaching system design**	**Proposed and demonstrated the functionality and the utility of the various concepts and artefacts**.	
2.1	Generic ACS framework and specific framework instances (Chapter 4).	Resulting connectionist method for modelling motion data analysis from the thesis. Incremental, evolving modular design approach to automating qualitative aspects of performance analysis.	All
2.2	Feature Selection (FS) and Feature Extraction Technique (FET).	Strategic algorithm design and properties influenced by surrounding constraints of augmented coaching system design and data contexts.	ACS, CI
2.3	Motion sequence design pattern: Temporal and spatial FET for qualitative assessment automation.	Generic algorithm design approach that relates to motion data transformations to targeted motion event and coaching rules. Identified a software design pattern integral to MoHEM/CREMs. See also mental model for motion sequence design pattern (7.4).	ACS, CI
3	**Case studies**	**Conducted two complementary case studies to provide supporting and practical evidence**.	

Contribution		Description, relevance and significance	Specific discipline
3.1	Tennis case study (Chapter 6).	Focus on connectionist methods and modelling various assessments of tennis coaching rules, tennis stroke recognition and feature extraction techniques.	ACS, CI, KD, K
3.2	Golf case study (Chapter 7).	Focus on data analysis of critical features of a 'swing plane' in golf.	CI, KD, K
4	**Impact or action zone modelling**	**Interdisciplinary assessment related to performance, safety or various combined movement objectives**.	
4.1	Global performance assessment model (Chapter 6).	The implementation of the (first) hypothesis investigating machine assessment of performance of diverse (tennis) swings over relatively narrow time period or displacement segment within motion data.	CI
4.2	Human interpretable error diagnosis.	Extending global performance model and adapting models of qualitative analysis such as temporal observation and task sheet (Chapter 2 and 4). Adapting qualitative methods for performance assessment to ML.	ACS, CI, K
4.3	Coaching rules as *diagnostic outputs* (Chapters 3-6).	Critical features, heuristics and coaching rules are human interpretable and better suited than a large number of extracted (machine) rules.	ACS, CI, K, G
5	**Knowledge Discovery (Chapters 6 and 7)**	- *interpretative outcomes* -	KD
5.1	Impact/action zone assessment model.	If a machine can diagnose what 'a human eye cannot see', a coach may combine emphasised impact/action segment practice (together with full swing practice) to develop cognitive focus for impact/action 'feel' and possibly improve factors such as: consistency, adaptability and accuracy.	ACS, C, K, CI
5.2	'Swing plane' is not linear plane when seen as a 'room for error'.	Feature analysis of the golf swing plane collected data revealed that the impact zone had greater importance for error than the segments from the rest of the golf swing plane, as perceived in literature and by a sport equipment manufacturer's error indicating method.	K, SE, KE
5.3	Swing width assessment.	Interpreting results of diverse algorithms enabled knowledge discovery related to the pelvis area observation for coaching. A coach may pay attention to the whole hip region (which is typically occluded when e.g. feeding the ball) to identify potential risks of injury or to maximise swing impact performance.	ACS, K, CI

Contribution		Description, relevance and significance	Specific discipline
5.4	Novice and advanced beginners tend to drive 'slice'.	Findings obtained from data analysis from participating subjects. Beginners program was focused on the grip, stance, swing and 'ball flight' qualitative properties (KP) rather than direction and distance outcome (KR). Beginners to intermediate players (not limited to) may buy a club designed to compensate for slice or have adjustable properties to compensate for ball trajectory between the target-line and slice direction. For golfers who may have difficulty to modify their standard golf swing (to control 'hook', 'pull', 'push' or 'slice', the logical choice on the golf course would be to compensate the stance relative to target line to compensate the likelihood for a ball trajectory between 'straight' or 'slice'.	SM, C, K, KE
6	**Tools**	**Utility of various concepts and artefacts**.	ACS, CI, ICT, G, SE
6.1	Validation incident prediction formula.	Statistical tool applicable for: modelling on relatively small data sets; *Subspace modelling* of a particular coaching rule may not have available balanced data set. Validation incident distribution for pre-clustered data (Chapter 7). Indication of data set size validation strategy, therefore contributing to overall modelling of motion data and related problem areas.	Statistics – Probability, CI
6.2	*External synchronisation for visualisation and replay* for qualitative analysis and CI modelling.	Generic viewing capability for video based coaching and qualitative analysis – with ability to communicate to CI modelling tools and operating environments. Mental model of operating a VCR - replay qualitative analysis. Interactive and portable 3D viewer/video implemented with extended VCR - replay usability features. A viewer model communication and integration with other environment for modelling and data analysis purposes (Chapter 5 and Appendix).	ACS, G, C, K
6.3	Automated golf data extraction.	A tool to extract automatically golf swing data, within compliance to golf manufacturer's end-user licensing agreement. Human data entry error was eliminated.	K, KE

Contribution		Description, relevance and significance	Specific discipline
6.4	Architecture and GUI platform for multidiscipline analysis and learning.	A demo prototype (applicable to connectionist models linked to Chapter 6) and the multi-tier application supporting personalisation and the user profiles for coaching, learning, qualitative analysis and incremental/evolving architecture modelling. Modular assessment and integrative modelling concepts and approaches. Multi-tier support for state and session between GUI, MATLAB COM server and 3D viewer (Chapter 5 and Appendix). Enabled evolving weighted modular architecture.	All
6.5	Impact or action zone as holistic assessment model.	Global assessment model to categorise tennis swings into discrete categories ('good' and 'bad').	ACS, CI
6.6	Automated assessments modules (MoHEM/CREM) for:	1) Stance assessment feature extraction method. Generic static and dynamic stance (around impact/action) conversion producing angle (with monotone increase) and body orientation (specific to racquet sports swings) as machine features. 2) Spin and velocity connectionist assessment method. Machine feature for classifying ability of (hand) movement to produce top-spin in racquet sports, similar to *kinesthetic proprioception* of a swing – extending it to human 'feel' for the outcome without measuring: the ball rotation outcome or physical properties such as elastic deformation, surface friction or rebound. Tennis coaches may refer to it as 'low to high' cue. 3) Swing width assessment. Performance vs. safety - flexible assessment criteria based on supervised learning and flexible assessment criteria. Interpreting results of diverse algorithms enabled knowledge discovery related to pelvis area observation for coaching.	ACS, C, K, CI
7	**Mental models and concepts**	**Graphic representations aiming to: (1) guide various aspects of coaching, explanation, design integration or application focus; and (2) assist with remembering the intricacy of cross-discipline insights after returning to the field.**	
7.1	Motion capture infrastructures.	Considerations for design and integration of augmented coaching systems and virtual environments (Figure IV-14).	ACS, K, G, ICT, SE, SM,

Contribution		Description, relevance and significance	Specific discipline
7.2	Coaching scenario flexible assessment modelling.	Flexible assessment criteria to improve various learning aspects. Performance criterion is subject to top down (goal) and bottom up (critical features) assessment – linked to flexible ML assessment and HMMA.	ACS, K, C
7.3	Classifier modelling considerations.	The elements of classifier modelling on features from motion data emerged from the case studies (Chapters 6 and 7).	ACS, CI
7.4	*Motion sequence* design pattern, FS and FET.	Temporal and spatial techniques for machine features modelling and critical analysis related to human motion data. Transforming motion data to relevant extracted machine features, features optimisation and assessment model architecture is viewed as the most complex interdisciplinary process and reported across the thesis from diverse perspectives. Utilised FET were based on: (1) processing of a subset of markers that are not necessarily from adjacent parts of the body or proximal-to-distal sequencing – from slow-moving to faster-moving segments; (2) temporal sub-phasing that are not strictly bound to phases (preparation, action, follow-through); and (3) spatial ML patterns.	ACS, CI, K
7.5	*Subspace modelling* and *orchestration.*	*Problem space* partitioning subject to prior analysis. Prior analysis is intended to reduce *problem space* dimensionality for modelling purposes and to produce flexible assessment and *diagnostic outputs* matched to heuristics and coaching rules.	ACS, CI, K
7.6	*Subspace modelling* for global, personalised and coaching scenario.	*Subspace modelling* for global assessment may utilise evolving and traditional ANN. Coaching scenario *subspace modelling* and assessment may be mapped to skill level, drill or personal circumstances such as recovery programme.	ACS, CI, K, C
8	**Providing coaching experience to an end-user**	**Findings and capabilities from this thesis** (e.g. application of automated qualitative assessment in gaming and augmented environments) and GUI prototype represent the opportunity to combine embedded and ubiquitous motion capture sensors (e.g. Microsoft's Kinect, 'Hawk-eye' and surveillance technology) for the purpose of providing real-time coaching experience in digital entertainment systems, sport/rehabilitation immersive virtual reality environments and motion based gaming.	All

Appendix B:

Thesis Notations, Symbols and Formulas

Sets of Numbers

N ... the set of *Natural* numbers, $N = \{1,2,\ldots\}$.

$\Re$, R ... the set of *Real* numbers.

$[n]$ ... compact notation for $\{1, \ldots, n\}$.

Data

U ... the *Universe* of all possible data.

X ... the input domain.

$x \in [x_{\min}, x_{\max}]$ ... notation for interval [x_{min} to x_{max}] or $x_{\min} \leq x \leq x_{\max}$.

Motion Data Calculus

Position = (x, y, z) as a point in 3D space.

Distance = $(\Delta x, \Delta y, \Delta z)$ as a vector or as a scalar i.e. $\sqrt{\left((\Delta x)^2 + (\Delta y)^2 + (\Delta z)^2\right)}$.

Velocity = $(\dot{x}, \dot{y}, \dot{z})$.

Acceleration = $(\ddot{x}, \ddot{y}, \ddot{z})$.

Note: the notation $\dot{x}$ represents the first derivative of x with respect to time as

$$\dot{x} = \frac{dx}{dt} \text{ or } \dot{x} = \frac{\Delta x}{\Delta t},$$

where $\dot{x}$ is a difference between two points $\Delta x = (x_{i+1} - x_i)$ measured in time interval $\Delta t = (t_{i+1} - t_i)$.

The notation $\ddot{x}$ represents the second derivative of x with respect to time as

$$\ddot{x} = \frac{d^2 x}{dt^2} \text{ or } \ddot{x} = \frac{\Delta \dot{x}}{\Delta t}.$$

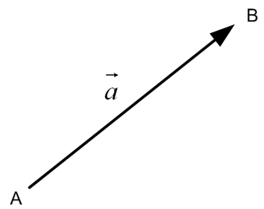
Scalars, Vectors and Matrices

In this thesis, unless defined otherwise, the identifiers in algorithms and in programming are as documented as follows:

- Lower case first letter in identifier denotes scalar variables (e.g. *i, lastFrame*);
- Upper case first letter in identifier denotes objects and other programming structures including *n*-dimensional arrays (e.g. *Z, Xmotion_vector*).

Identifier with all letters in upper case: Fixed values, programming constants, reserved words representing common programming constructs (e.g. IF, WHILE).

In this thesis, vector calculations are used in biomechanics calculus and machine feature extraction algorithms. Scalars are single values that can be expressed with positive and negative amounts such as weight, height, temperature. Vectors are values and directions determined as projections in *k*-dimensional space such as force, speed, acceleration. Depending on circumstances and in diverse disciplines, a vector (see below) may be denoted as $\overrightarrow{AB}$ or $\vec{a}$ or simply as a.



$\vec{v}$ … vector $\vec{v} = \begin{bmatrix} v_1 & \cdots & v_k \end{bmatrix}$ of $(1,k)$ elements or $\vec{v} = \begin{bmatrix} v_1 \\ \vdots \\ v_k \end{bmatrix}$ of $(k,1)$ elements.

z … scalar $z = \begin{bmatrix} v_1 & \cdots & v_k \end{bmatrix} \cdot \begin{bmatrix} v_1 \\ \vdots \\ v_k \end{bmatrix}$.

z … is a single element value e.g:

The length z of vector $\vec{v}$ is $z = \|v\| = \sqrt{\vec{v}^T \vec{v}} = \sqrt{\Sigma_{i=1}^{k} v_i^2}$.

Appendix B

$X \ldots$ matrix $X = \begin{bmatrix} v_1 \\ \vdots \\ v_k \end{bmatrix} \cdot \begin{bmatrix} v_1 & \cdots & v_k \end{bmatrix}$ of $k \times k$ elements.

$X \ldots$ matrix $X = \begin{bmatrix} x_{1,1} & \cdots & x_{1,n} \\ \vdots & \ddots & \vdots \\ x_{m,1} & \cdots & x_{m,n} \end{bmatrix}$ of $m \times n$ elements.

The scalar p between the two vectors $\vec{a}, \vec{b}$ of $(k,1)$ elements is:

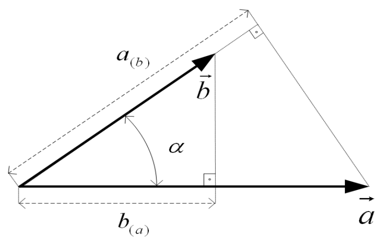
$p = \vec{a}^T \vec{b} = \vec{b}^T \vec{a} = a_1 b_1 + \ldots + a_k b_k$.

The angle between the two vectors $\vec{a}, \vec{b}$ of $(k,1)$ elements is:

$$\cos(\alpha) = \frac{\vec{a}^T \vec{b}}{\|a\| \|b\|} = \frac{a_1 b_1 + \ldots + a_k b_k}{\sqrt{a_1^2 + \ldots + a_k^2} \sqrt{b_1^2 + \ldots + b_k^2}}.$$

If $\cos(\alpha) = 0$ then the two vectors are orthogonal.

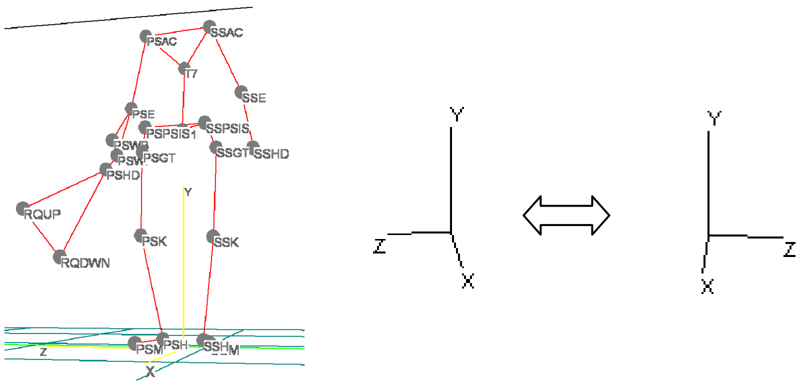
The projection of one vector on the direction of the other (scalar or dot product):



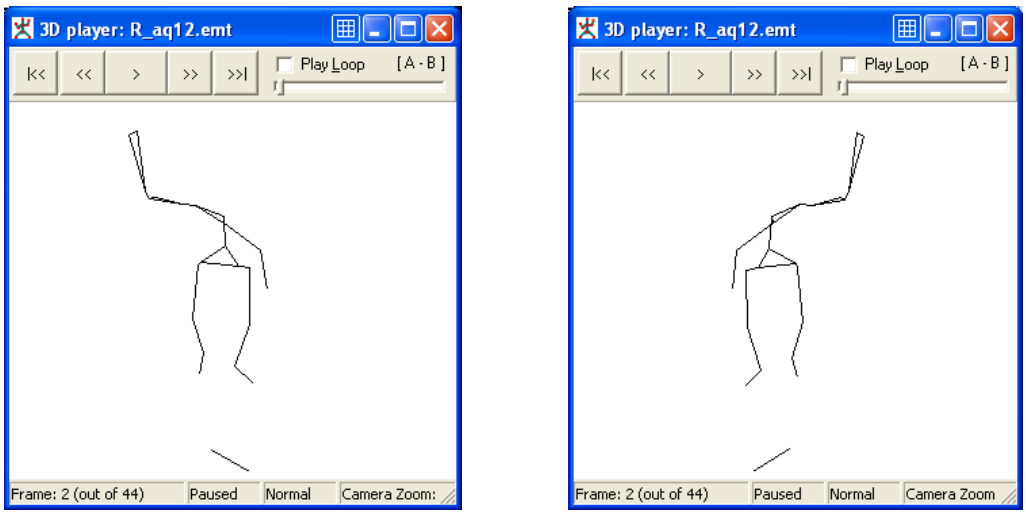
$\vec{a}^T \vec{b} = \|a\| b_{(a)} = \|b\| a_{(b)}$.

Change the Coordinate System

For cases where acquired data and viewing tool are using different coordinate systems, the transformation below is resulting in 'mirror' effect. This observation can be used for left-handed player data to be converted and processed as a right handed for *machine learning*.



Right-handed 3D space   Left-handed 3D space



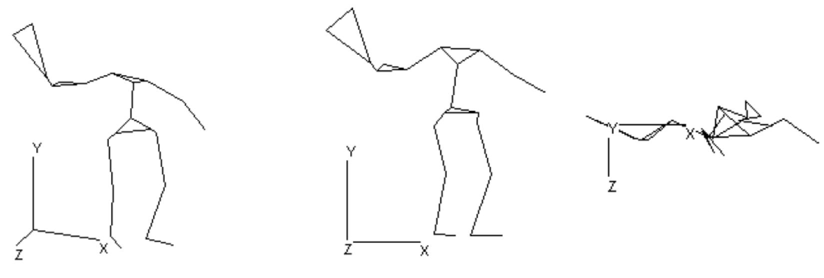
Right-handed 3D space can be translated to left-handed by changing the sign for z-axis values.

Note: 3D space and transformation matrices are common in computer graphics (outside of the scope of the thesis).

For left-handed players, appropriate video replay (e.g. coaching by comparisons) can also be achieved by swapping line pixels horizontally within each frame.

Viewing Anatomical Reference Planes

Replay function with virtual camera view of observed region of interest is important usability feature for qualitative human analysis.



Randomly chosen camera view | Sagittal view | Transverse view | Frontal view

Directional Reference and 3D stick figure views of a tennis player.

Vertical Rotation

For cases in which the approximate 'target line' may not be parallel with *x-axis*, the markers data set can be rotated in *xz-plane* to offset the angle δ between intended target line and x-axis. For example, a 3D marker point $p = (x, y, z)$ results in transformed marker point $p_{transf} = rotate(p, \delta)$, as shown in the algorithm below:

Algorithm: $rotate(p, \delta)$

// Rotate 3D markers' data around y-axis for angle (δ) :

1: $$p_{transf} \leftarrow \begin{bmatrix} x \cdot \cos(\delta) & 0 & z \cdot \sin(\delta) \\ 0 & y & 0 \\ -x \cdot \sin(\delta) & 0 & z \cdot \cos(\delta) \end{bmatrix} \cdot \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}$$

2: RETURN (p_{transf})

Appendix B

Random Sampling from Internalised Input Data Clusters and Output Classes – Novel Probability Formula and Rationale

P(C) probability of event *C* formula:

$$P(C) = \frac{\binom{j}{k}\binom{n-j}{m-k}}{\binom{n}{m}}$$

Where:

P(C) … probability of event C	*n* … size of the sample space *S*
A … entire cluster selected for testing, $k = 0$	*S* … sample space, $S = \{1,2,\ldots n\}$
B … one sample is selected for training, $k = 1$	*j* … size of the observed cluster
C … *k* cluster samples are selected for testing	*m* … size of the test data set *M*
D … entire cluster selected for training, $k = j$	*k* … number of samples in test data from observed cluster.

Formula rationale:

$$P(C) = \frac{(possible\,k\;cluster\_members)(no.of\_other\,(m-k)\;possible\_non\_cluster\_members)}{(no.of\_all\_possible\_combinations\_in\_test\_dataset)}.$$

The formula above can be also be used for expert's internalised grouping such as (backhand, forehand, open stance, closed stance) as well as for the clusters and output class/labels, such as (good, bad) swing.

Split-sample Validation Simulation

Prior to simulation, random generator for uniform distribution has been tested for the experiment purposes. Simulation refers to *holdout* validation method i.e. by selecting elements for test data set without replacement, disregarding selected elements order.

Simulation data:

Data samples = 40
Clusters = 9
Holdout split = 35 samples for training and 5 for testing.

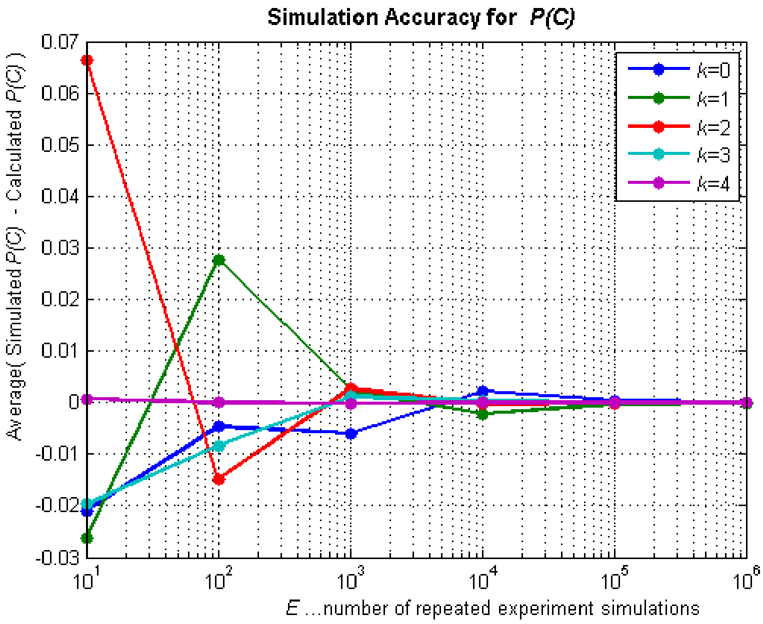
Cluster 7 have 0 elements and is there for control purposes. Five clusters have size 5, two clusters have size 4 and cluster 6 has 7 samples.

Analytical results for holdout validation.

k	*P(C,j=4)*	*P(C,j=5)*	*P(C,j=7)*	**Comment**
0	0.5729	0.4937	0.3607	Cluster data not tested; *P(D)*.
1	0.3581	0.3979	0.4353	Desired case for small clusters.
2	0.0651	0.0995	0.1741	Possible incident or desired case.
3	0.0038	0.0090	0.0281	Incident; *P(B)*.
4	0.0002	0.0003	0.0018	Incident; *P(A)* and *P(B)*.
5	N/A	1.519e-6	3.191e-5	Incident *P(D)* for small clusters.

Calculation and simulation results (repeated experiments snapshot at E = 100,000).

```
Probability holdout Simulation Results
      k    P(C,j=4)   P(C,j=5)   P(C,j=7)
      0    0.5722    0.4930    0.3621
   1.0000    0.3595    0.3979    0.4355
   2.0000    0.0644    0.0997    0.1729
   3.0000    0.0039    0.0091    0.0280
   4.0000    0.0000    0.0003    0.0016
   5.0000        0           0         0.0000

Probablility Calculation Results
      k    P(C,j=4)   P(C,j=5)   P(C,j=7)
      0    0.5729    0.4934    0.3607
   1.0000    0.3581    0.3979    0.4353
   2.0000    0.0651    0.0995    0.1741
   3.0000    0.0038    0.0090    0.0281
   4.0000    0.0001    0.0003    0.0018
   5.0000       NaN     0.0000    0.0000

Start experiment: 25-Nov-2006 02:31:05
End   experiment: 25-Nov-2006 02:43:58
Time elapsed:          746.10 [s]
% Difference
>> out = Sim - Calc
out =
      0   -0.0007   -0.0004    0.0014
      0    0.0014         0         0.0002
      0   -0.0007    0.0002   -0.0012
      0    0.0001    0.0001   -0.0001
```



Simulations differences from calculated and simulation values seem to disappear after large number (> 10^5-10^6) of repeated *holdout* validation experiments.

Reporting Classification and Event Recognition Results

As shown in Chapter 7, where appropriate, reporting of classification results may include: (1) bar graph (i.e. *individual class accuracy histograms*) showing classification accuracy per individual output class, (2) *confusion table* (see table below).

Confusion table.

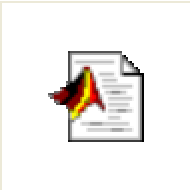
	Actual class	
Predicted class	*True_Positive*	*False_Positive*
	False_Negative	*True_Negative*

$$Overall\_Accuracy = \frac{(True\_Positive)+(True\_Negative)}{(True\_Positive)+(True\_Negative)+(False\_Positive)+(False\_Negative)}.$$

Where:
True_Positive, *True_Negative* … number of correctly classified data samples
False_Positive, *False_Negative* … number of incorrectly classified data samples.

Appendix C: Code Resources

Sample code (MATLAB® ver. 7.1) for probability and correlation matrix from golf data (see Chapter 7).



Correlation.m

Correlation (Golf_data)

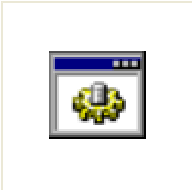
```
%% Correlation
% Author  : Boris Bacic
% Purpose : Comparing NeuCom and Matlab results demonstration
%
% Excerpt from MATLAB Help - see command below:
% help corrcoef
% ...
% 'alpha'   A number between 0 and 1 to specify a confidence level of
%           100*(1 - alpha)
%           Default is 0.05 for 95% confidence intervals.
% Matrices:
%           RLO and RUP
%                      are of the same size as R, containing lower and
%                      upper bounds for a 95% confidence interval for
%                      each coefficient.
%           P
%                a matrix of p-values for testing the hypothesis of
%                no correlation.
%                Each p-value is the probability of getting a correlation
%                as large as the observed value by random chance,
%                when the true correlation is zero.
%                If P(i,j) is small, say less than 0.05, then the
%                correlation R(i,j) is significant.
%                [i,j] = find(P < 0.05);  % Find significant correlations.
%           R
%                correlation coefficients calculated from an input
%                matrix X whose rows are observations and whose columns
%                are variables.
%                The matrix R = corrcoef(X) is related to the covariance
%                matrix C = cov(X) by:
% ...
```

$$R_{i,j} = \frac{C_{i,j}}{\sqrt{C_{i,i} \cdot C_{j,j}}}$$

```
% Modfy read input Golf_data as needed ------------------

Golf_data = 'out_subclass_GOLF_shots_OK_v093_Linear_Normalised_1.txt';

disp('Loading data...')

importfile('out_subclass_GOLF_shots_OK_v093_Linear_Normalised_1.txt')
X = out_subclass_GOLF_shots_OK_v093_Linear_Normalised_1
% end of read input data ------------------------------

CR = sprintf('\n');
[R,P,RLO,RUP] = corrcoef(X);
disp(CR);
disp(['Probability = ' CR])
probability = num2str(P,'   %3.2f');
disp(probability);
disp(CR);
correlation = num2str(R,'  %3.2f');
disp(['Numeric Correlation = ' CR])
disp(correlation)


Probability =

1.00   0.00   0.18   0.00   0.00   0.09   0.00
0.00   1.00   0.92   0.00   0.00   0.00   0.49
0.18   0.92   1.00   0.01   0.00   0.00   0.00
0.00   0.00   0.01   1.00   0.00   0.00   0.02
0.00   0.00   0.00   0.00   1.00   0.32   0.00
0.09   0.00   0.00   0.00   0.32   1.00   0.00
0.00   0.49   0.00   0.02   0.00   0.00   1.00


Numeric Correlation =

 1.00    0.56  -0.06    0.25    0.45  -0.07    0.15
 0.56    1.00  -0.00    0.85    0.52  -0.34    0.03
-0.06   -0.00   1.00    0.12    0.16    0.83    0.32
 0.25    0.85   0.12    1.00    0.53  -0.19    0.10
 0.45    0.52   0.16    0.53    1.00    0.04    0.56
-0.07   -0.34   0.83   -0.19    0.04    1.00    0.31
 0.15    0.03   0.32    0.10    0.56    0.31    1.00
```

ASCII file 3D motion data sample-rows extraction

Motion data extraction source code for Microsoft's Windows OS family. Motion data must be in text format, each row representing a captured frame sample. For safe program operation, it is recommended to use short file naming convention (also known as 'DOS 8.3').

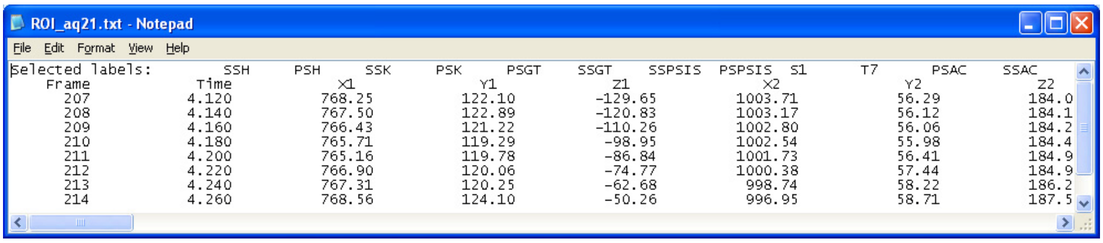


Extract.bat

Extract Source_file Start_Frame End_Frame

```
@echo off
REM Author: Boris Bacic
REM Sep. 2003.
REM Purpose: Extract adjacent horizontal portion of 3D tracks from ASCII EMT file.
REM Caveats: Avoid illegal characters for naming of data files.

set SOURCE_FILE=%1
set START_FRAME=%2
set END_FRAME=%3
set STEP=1
REM Uncomment and modify the following 2 lines if adding more input options
::if %1.#==.# goto help
::if "%1"=="/?" goto help
if NOT DEFINED SOURCE_FILE goto help

REM uncomment and modify the following 2 lines if you need headers in exported file
:: find /i "Selected labels:" < %SOURCE_FILE%
:: find /i "Frame    " < %SOURCE_FILE%

REM the first column of motion file refers to the frame number, which is used for extraction
for /L %%i in (%START_FRAME%,%STEP%,%END_FRAME%) do find "    %%i          " < %SOURCE_FILE%
goto end
:help
  echo Purpose:
  echo %0 source_file start_frame end_frame
:end
  set SOURCE_FILE=
  set START_FRAME=
  set END_FRAME=
  set STEP=
```

Note: Inline with *external synchronisation for visualisation and replay*, this programme can be invoked from DOS command line or from the modelling environments such as MATLAB®.



```
ROI_aq21.txt - Notepad
File  Edit  Format  View  Help
Selected labels:       SSH      PSH      SSK      PSK      PSGT     SSGT     SSPSIS   PSPSIS   S1       T7       PSAC     SSAC
    Frame              Time              X1                Y1                Z1                X2                Y2       Z2
     207              4.120            768.25            122.10           -129.65           1003.71            56.29    184.0
     208              4.140            767.50            122.89           -120.83           1003.17            56.12    184.1
     209              4.160            766.43            121.22           -110.26           1002.80            56.06    184.2
     210              4.180            765.71            119.29            -98.95           1002.54            55.98    184.4
     211              4.200            765.16            119.78            -86.84           1001.73            56.41    184.9
     212              4.220            766.90            120.06            -74.77           1000.38            57.44    184.9
     213              4.240            767.31            120.25            -62.68            998.74            58.22    186.2
     214              4.260            768.56            124.10            -50.26            996.95            58.71    187.5
```

3D motion data – ASCII file layout.

Running instructions

Copy the source code in e.g. notepad and save as BAT or CMD file (e.g. extract.bat).

Save the program (e.g. extract.bat) to a folder containing motion data (e.g. "D:\Current Work\data").

Copy the motion data folder path into a clipboard (e.g. "D:\Current Work\data").

Open a command line window and change directory to the motion data folder (e.g. "D:\Current Work\data"):

<Window key> R
cmd /k cd /d "D:\Current Work\data"
In text based console, type the command below:

Extract filename start stop
or

Extract filename start stop >> outputFilename

Where:

filename	... is a motion data file name,
start and **stop**	... represent corresponding row numbers,
outputFilename	... is extracted motion event file. If not specified output data will be displayed on screen or in MATLAB command window.

MATLAB code required to integrate the program with its environment:

! Extract filename start stop
or

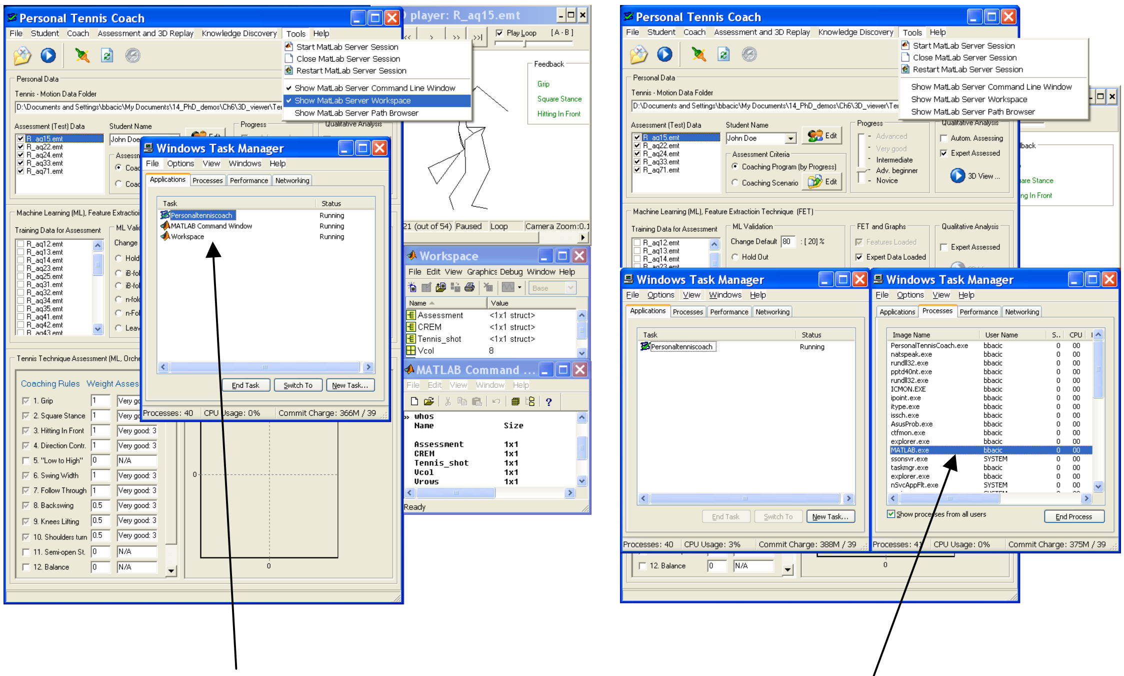
eval(['! Extract ' filename num2str(start) num2str(stop)])

Appendix D:

Data Viewing and Distributed Processing

Interactive MATLAB™ Functionality of a Back-end COM Server

The back-end functionality allows access to modify intermediate data during the processing session with the GUI front-end. Such functionality allows performing additional functions over data including various graphs display.



a) Back-end enabled for 'power-user' requirements.

b) GUI front-end is visible, while hiding background processing of windows processes.

Background process visibility in a) and b) menu options. The front end hides or allows direct interaction with MATLAB™ back-end. The session control allows access to intermediate processing data.

APPENDIX E:

Expert Validation and Ethics Approval

Expert Validation Summary

The separate informal interviews with two coaches included a presentation of: video (see supplementary CD, 'User Interface Augmented Coaching.mov'), use of software (Chapters 5 and 6) and motion data (Chapter 6). Both coaches gave their permission for their short biographies and their comments to be included in this thesis appendix.

Coaches' Biographies

Shelley Bryce (nee **Stephens**), Resident head coach at Milford Tennis Club, since 2005 and also a coach at Tennis Northern regional junior academy. She was a professional tennis player for ten years and was number one in New Zealand for five years, with international rankings of 246 in singles and 132 in doubles. Shelley is also a selector and manager for the national for U12s, U14s and women's Federation Cup teams. Shelley also managed the winning Milford women's Chelsea Cup team. Shelley was selected by Tennis Northern as rep team coach for the U12 age group at the National Teams Event. She is also a national coach and coordinator including travels with NZ girls U16 team. She has been recognized as the Coach of the Year 2012 for Tennis Northern. Shelley provides coaching pathways for several junior players and coaches, training young players as assistant coaches.

Kevin Woolcott, Resident coach at Forrest Hill Tennis Centre, Auckland for the past eighteen years. He is the co-founder and a director of Tennislife Coaching (www.tennislife.co.nz). Kevin is a strong believer in coaching education and application of technology to augment coaching. He was the chairman of Coaching New Zealand for the two terms (four years) in the early 90's and is a life member of Tennis Coaching New Zealand (TCNZ). Kevin's roles in tennis after playing internationally have included Tennis New Zealand national coach (six years), Fed Cup coach captain and World Youth Cup coach. Kevin was also a member of the United States Professional Tennis Association (USPTA). Kevin is one of the first coaches who utilized and shared his expertise with siliconCOACH and timeWARP software in his coaching and influenced the most recent ISBS 2012 publication associated with my PhD and augmented coaching software.

Interview Background

During the informal interview the coaches viewed the demo material including:

1. The "Personal Tennis Coach" video – introducing the thesis concepts,
2. Software demo – associated with the tennis coaching case study, and
3. Tennis swings data – reviewed all tennis swing samples, prior assessment and similarity grouping.

After viewing the video, each coach reviewed the use of the interactive software and the data views available with the assistance of the author of this thesis. Each coach focused on high-level operations including data similarity grouping and diagnostic tasks associated with the tennis swing data. For example, both coaches directed the desired vantage points for virtual camera views and change of speed during the loop replay. When shown data similarity groupings, both coaches agreed to the swing grouping that was arranged before the demonstration. The software demonstration also included the use of the "Personal Tennis Coach" and a stand-alone 3D player (see the supplementary CD: StickFigure_Player.exe) related to possible usage scenarios and assessment reporting.

The open-ended questions included the following:

1. In your opinion, can this software be used for coaching and what other potential use may you see?
2. In your opinion, can a 3D stick figure be used for recognizing swing patterns and qualitative replay analysis of the selected coaching rules? Any comments on using the stick figure data and 3D software?
3. Tennis swing samples data – do you agree with swing patterns and grouping based on the similarities? Any comments related to good swings and common errors?

Coaches comments – the summary of the tennis coaches' comments after viewing the video, software and tennis data.

Coaches' comments	**Shelley Bryce**	**Kevin Woolcott**
I would like to use the on-line version of the prototype with my assistant coaches. They would be able to have support for autonomous error detection consistent with my subjective criteria.	√	√
I would be able to share my coaching philosophy (e.g. grip, stance and swing patterns) and to improve management of my assistant coaches teaching at different coaching scenarios and levels from beginners to intermediate.		√
I would be able to personalise my coaching for diverse groups, goals and skill levels.	√	
I agree with the first coach's assessment of tennis swing data including similarities of group patterns.	**100%**	**100%**
I recognised common errors in motion data that are common for novices to intermediate levels. I also agree on 'very good' swings group selection and their demonstration.	**100%**	**100%**
I can use 3D animated stick figure replay to assess tennis swings. I like interactive replay from different angles.	√	√
I am keen to immediately use the demo software and available 3D stick figure data in my coaching to show 'hard-to-learn' critical concepts using 3D interactive features. In particular, I acknowledge the high demonstration standard of the swing samples included in the category 'very good'.		√*
To reach a wider number of players I would be keen to use motion acquisition to combine demonstrated interactive 3D stick figure replay with automated 'progressive achievement' functionality.		√*
I would recommend commercialising this software and data. This would also include extending it to smart phone/tablet technology.		√*
I would recommend improving the 3D stick figure with fast and short loop replays without the pause and sense of orientation when using front and rear views.		Need improvement

√*) Background: I have used a variety of software for video coaching and I have also worked with injured tennis players to help them through their personal rehabilitation program. In the past, before using siliconCOACH, I hired a software developer to develop a "stick figure" drawing for automating the reports on students' progress and to develop presentation materials for coaching. Being responsible for running a coaching business, reporting was too time-demanding to be considered as rewarding when managing the large groups of students.

MEMORANDUM

Auckland University of Technology Ethics Committee (AUTEC)

To:	Nik Kasabov
From:	**Madeline Banda** Executive Secretary, AUTEC
Date:	2 March 2007
Subject:	Ethics Application Number 06/105 **Golf data acquisition for computational modelling of coaching process.**

Dear Nik

I am pleased to advise that the Chair and I as the Executive Secretary of the Auckland University of Technology Ethics Committee (AUTEC) have approved an amendment to your ethics application allowing the experiment to be conducted with two or more repetitions per participant and removing the provision of feedback by an NZPGA golf pro. This delegated approval is made in accordance with section 5.3.2 of AUTEC's *Applying for Ethics Approval: Guidelines and Procedures* and is subject to endorsement at AUTEC's meeting on 12 March 2007.

I remind you that as part of the ethics approval process, you are required to submit to AUTEC the following:

- A brief annual progress report indicating compliance with the ethical approval given using form EA2, which is available online through http://www.aut.ac.nz/research/ethics, including when necessary a request for extension of the approval one month prior to its expiry on 6 June 2009;
- A brief report on the status of the project using form EA3, which is available online through http://www.aut.ac.nz/research/ethics. This report is to be submitted either when the approval expires on 6 June 2009 or on completion of the project, whichever comes sooner;

It is also a condition of approval that AUTEC is notified of any adverse events or if the research does not commence and that AUTEC approval is sought for any alteration to the research, including any alteration of or addition to the participant documents involved.

You are also reminded that, as applicant, you are responsible for ensuring that any research undertaken under this approval is carried out within the parameters approved for your application. Any change to the research outside the parameters of this approval must be submitted to AUTEC for approval before that change is implemented.

Please note that AUTEC grants ethical approval only. If you require management approval from an institution or organisation for your research, then you will need to make the arrangements necessary to obtain this. Also, should your research be undertaken within a jurisdiction outside New Zealand, you will need to make the arrangements necessary to meet the legal and ethical requirements that apply within that jurisdiction.

To enable us to provide you with efficient service, we ask that you use the application number and study title in all written and verbal correspondence with us. Should you have any further enquiries regarding this matter, you are welcome to contact Charles Grinter, Ethics Coordinator, by email at charles.grinter@aut.ac.nz or by telephone on 921 9999 at extension 8860.

On behalf of the Committee and myself, I wish you success with your research and look forward to reading about it in your reports.

Yours sincerely

Madeline Banda
Executive Secretary
Auckland University of Technology Ethics Committee

Cc: Boris Bacic boris.bacic@aut.ac.nz, AUTEC Faculty Representative, Design and Creative Technologies

From the desk of ...
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page 1 of 1

Ethics approval (AUTEC number 06/105).

Appendix E

Ethics application timeline:

- First Submission: May 2006,
- Approval Granted: March 2007.

The main guidelines associated with the subjects' learning are:

1. Injury prevention. The Chapter 7 outlines the protocol for subject's warm-ups, data collection and post-stretching routine. Subjects were required to take at least one day rest between the practice sessions and to communicate any physical discomfort during and in-between the sessions.
2. Basic skill acquisition programme and learning were inline with NZPGA programme (allowing the subjects to continue their golf coaching programme) and with the augmented coaching software ("Leadbetter interactive," 2005).

During the golf experiment conducted in a case study (Chapter 7) the subjects would receive feedback in the form of a report document which combined data from the 3D SmartSwing ("SmartSwing," 2005) analysis and selected frames from captured video along with highlighted observed/measured critical features and desired critical features.

Appendix F: ICT Infrastructure and Utilities

The list of software and utilities developed in supporting this case study:

1. Tennis demo – multi-tier application.
2. Libraries:
    - Delphi - MATLAB session,
    - Memory handling and import of ASCII 3D data in Delphi,
    - MATLAB visualisations for: feature, motion data and data statistics,
    - 3D to 2D viewing prototypes developed in: MATLAB, Delphi and Lazarus (Linux/Ubuntu ver. 9.10 and 11.10, 64-bit).
3. External synchronisation for visualisation and replay with instructional feedback capabilities:
    - Animated 3D viewer with virtual camera interaction capability,
    - Media player (native DV video capture format with codec plug-in capability),
    - Modified VirtualDub for single-step video capture with capture file(s) auto naming.
4. Optimisation log spreadsheets (supporting data acquisition protocol):
    - Video capture parameters optimisation,
    - Battery life (charging and emptying dynamics of the SmartClub).
5. Miscellaneous utilities:
    - Remote mouse gesture recognition 'digital clapper board' for golf experiment,
    - Multistage SmartSwing PDF report to TXT data export utility,
    - ASCII file 3D motion data sample-rows extraction,
    - Unit converter to metric system for Golf experiment tools.
6. Data and backup utilities:
    - Project milestone undo/redo,
    - Multi platform data exchange and synchronisation,
    - SmartSwing incremental data backup supporting undo/redo.
7. Automated subjects' registration and information pack distribution via e-mail.