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ICIC 2013, Nanning

Evolving Computational Intelligence: Methods, Systems, Applications

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Abstract

The talk presents an overview of current methods of computational intelligence (CI) called evolving CI (eCI) and how they can be used in to create adaptive, computational intelligence (CI) systems across areas of applications. Evolving systems evolve their structure and functionality in a self-organised, adaptive, incremental way to capture patterns form input data. The methods presented include: evolving connections systems (ECOS) and evolving neuro-fuzzy systems in particular [1]; evolving spiking neural networks (eSNN) [2-5]; evolutionary and neurogenetic systems [6]; quantum inspired evolutionary computation [7,8]; rule extraction from ECOS [1] and eSNN [9].

The methods above are suitable for incremental adaptive, on-line learning from data and data mining. They are applied on spatio and spectro temporal data modeling and pattern recognition problems, including: moving object recognition, gesture- and sign language recognition [5]; bioinformatics [10]; ecological and environmental modeling, such as establishment and spread of invasive species [11]; cybersecurity [12]; brain data modeling and brain-computer interfaces [13]. eSNN have proved superior for spatio and spectro-temporal data analysis, modeling and pattern recognition (http://ncs.ethz.ch/projects/evospike/). Future directions for eCI are discussed including hardware-software system development and neuromorphic engineering [14].

Materials related to the lecture, such as papers, data and software systems can be found on the Knowledge Engineering and Discovery Research Institute KEDRI web site (www.kedri.info) of the Auckland University of Technology.

Content

1. Evolving Computational Intelligence

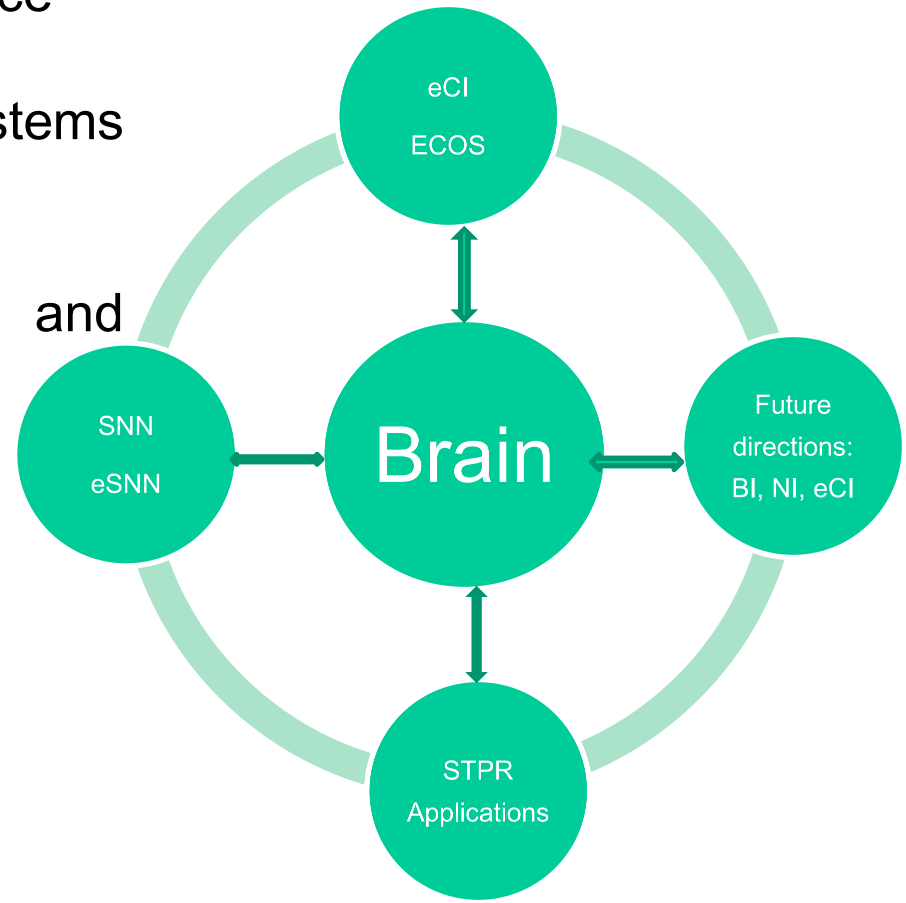
2. Evolving Connectionist Systems (ECOS)

3. Spiking Neural Networks (SNN) and eSNN

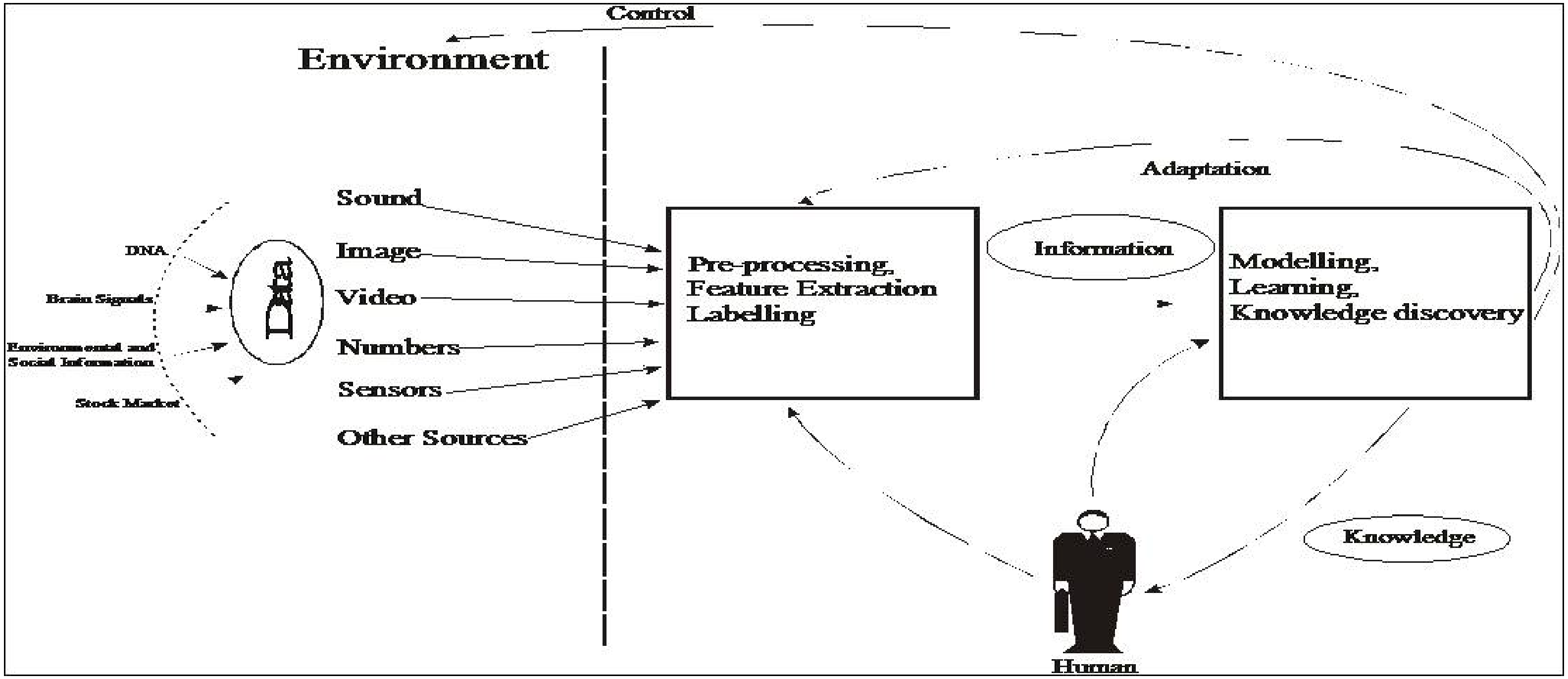
4. Applications for Spatio/Spectro-Temporal Pattern Recognition

5. Future directions

6. References



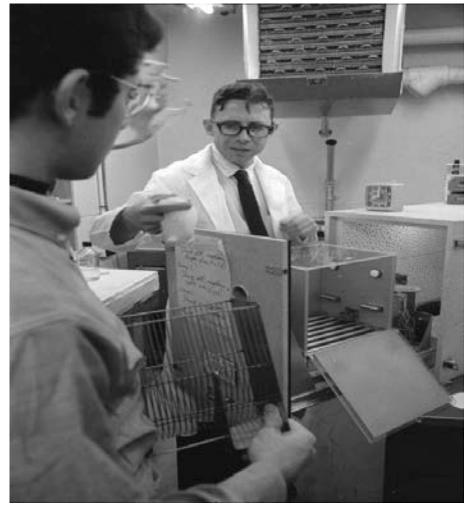
1. Evolving Computational Intelligence (eCI)

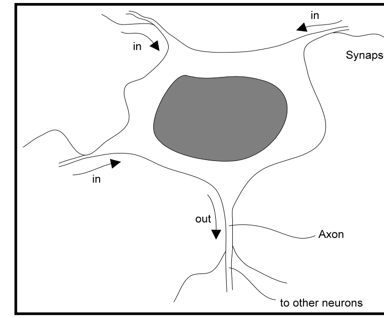


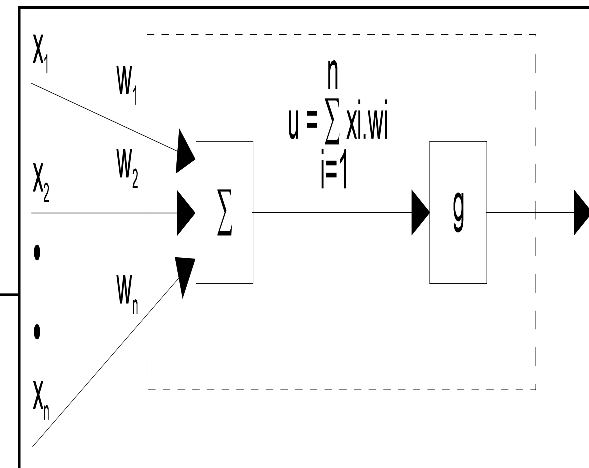
- Modelling complex processes is a difficult task: adaptation is needed based on new data and new information
- Knowledge discovery – always evolving, improving , changing
- A wide range of real-world on-line applications
- Nature inspired methods for eCI

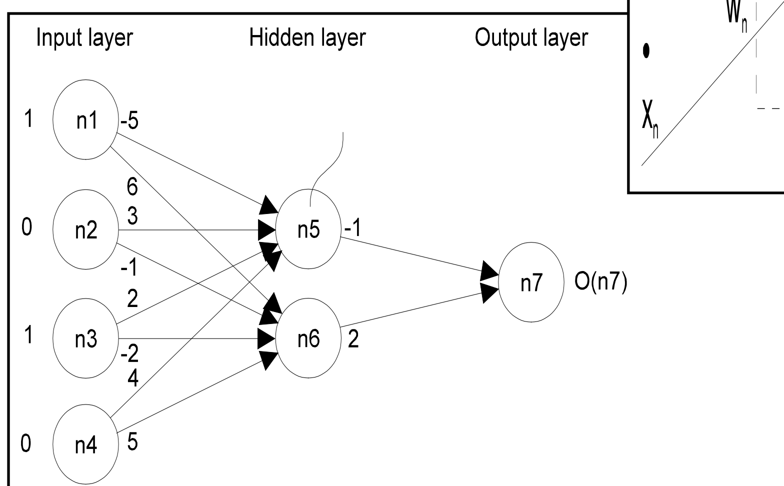
Brain –inspired adaptive ANN

- NN are computational models that mimic the nervous system in its main function of adaptive learning.
- Frank Rosenblatt (1928-1971), Perceptron, 1962
- ANN can *learn* from data and make *generalisations*
- ANN are *universal computational models*
- Software and hardware realisation of ANN
- Neurocomputing



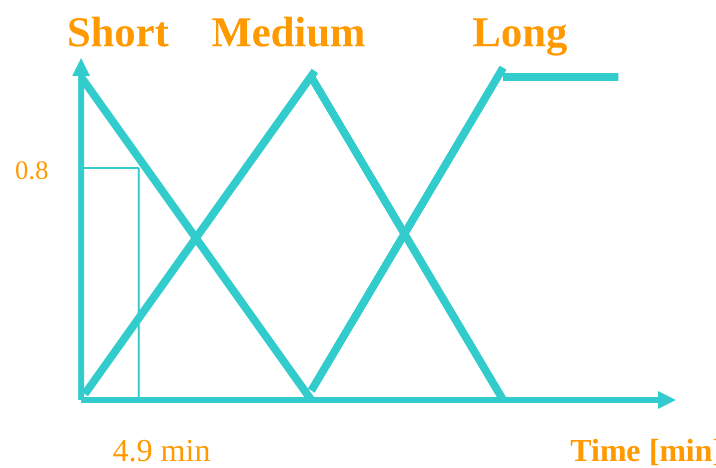






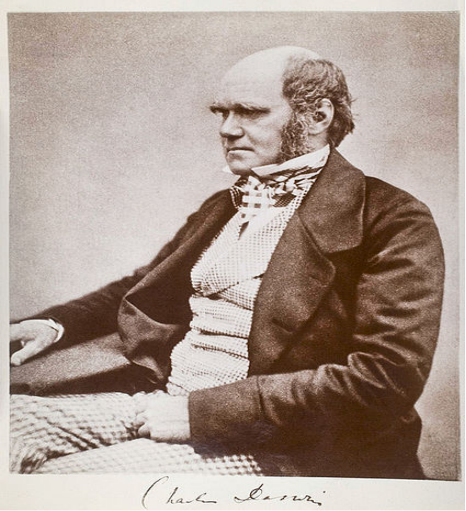
Evolving Fuzzy Systems for eCI

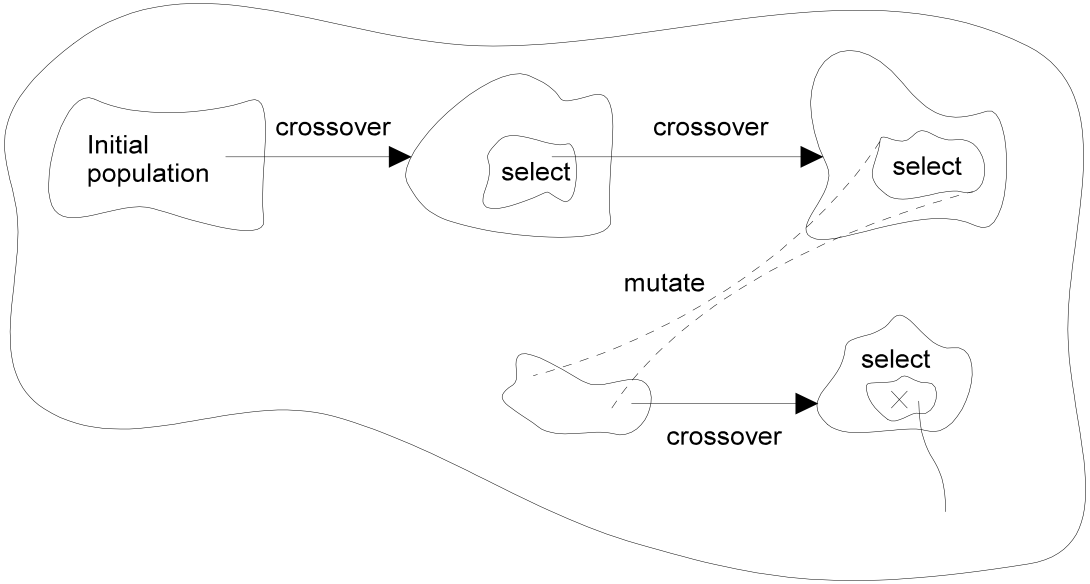
- Rigid propositional logic: Aristotle (4th century BC), e.g.: IF A and B THEN C (true or false)
- Fuzzy logic as an extension of propositional logic (L.Zadeh, 1965): If A is Small THEN C is Medium
- Fuzzy neural networks (Yamakawa, 1990; and others)
- Evolving fuzzy neural networks (EFuNN Kasabov, 1998; Angelov, 2002; others)



Evolutionary Computation for eCI

- Species develop through genetic evolution
- Survival of the fittest individuals
- Genes: carrier of information
- A set of chromosomes define an individual
- Population of individuals
- Generations of populations
- Crossover
- Mutation
- Fitness function
- Selection

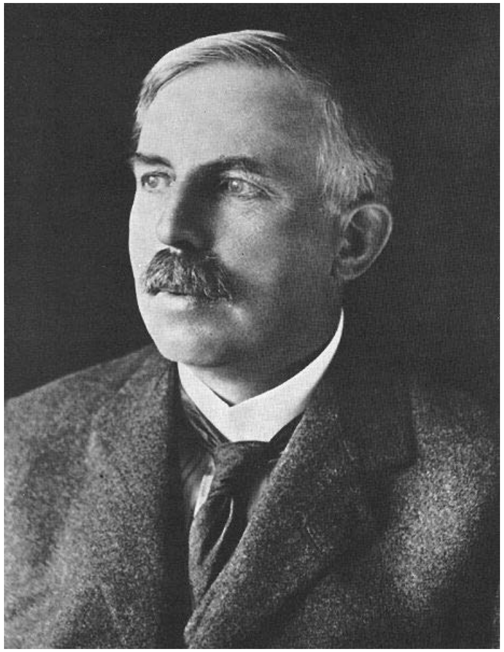




Quantum Inspired Technologies for eCI

- Quantum principles: superposition; entanglement, interference, parallelism
  - Quantum bits (qu-bits)

$$|\Psi\rangle = \alpha|0\rangle + \beta|1\rangle \qquad |\alpha|^2 + |\beta|^2 = 1$$



- - Quantum vectors (qu-vectors)

$$\begin{bmatrix} \alpha_1 & \alpha_2 & \cdots & \alpha_m \\ \beta_1 & \beta_2 & \cdots & \beta_m \end{bmatrix}$$

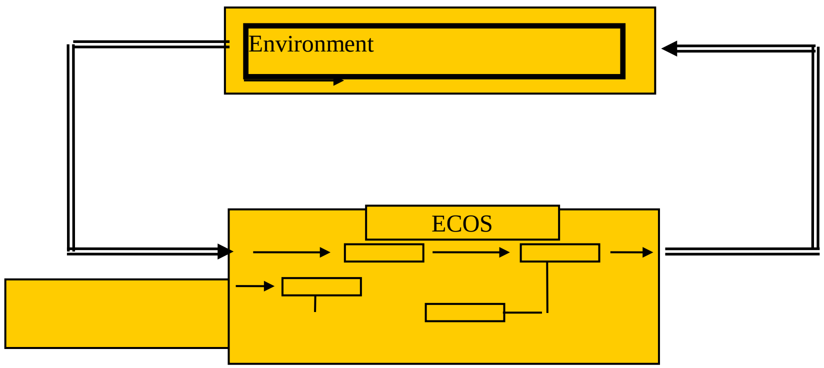
- Quantum gates

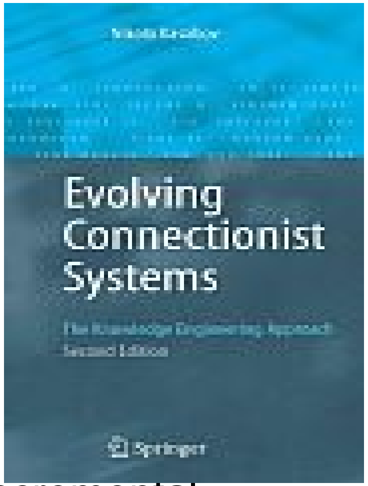
$$\begin{bmatrix} \alpha_i^j(t+1) \\ \beta_i^j(t+1) \end{bmatrix} = \begin{bmatrix} \cos(\Delta\theta) & -\sin(\Delta\theta) \\ \sin(\Delta\theta) & \cos(\Delta\theta) \end{bmatrix} \begin{bmatrix} \alpha_i^j(t) \\ \beta_i^j(t) \end{bmatrix}$$

- Applications:
  - Specific algorithms with polynomial time complexity for NP-complete problems (e.g. factorising large numbers, Shor, 1997; cryptography)
  - Search algorithms (Grover, 1996), $O(N^{1/2})$ vs O(N) complexity)
  - Quantum associative memories
  - Quantum inspired evolutionary algorithms and neural networks

2. Evolving Connectionist Systems (ECOS)

- ECOS are modular connectionist-based systems that evolve their structure and functionality in a continuous, self-organised, in on-line, adaptive, interactive way from incoming information facilitating knowledge discovery (Kasabov, 1998, 2002, 2007).





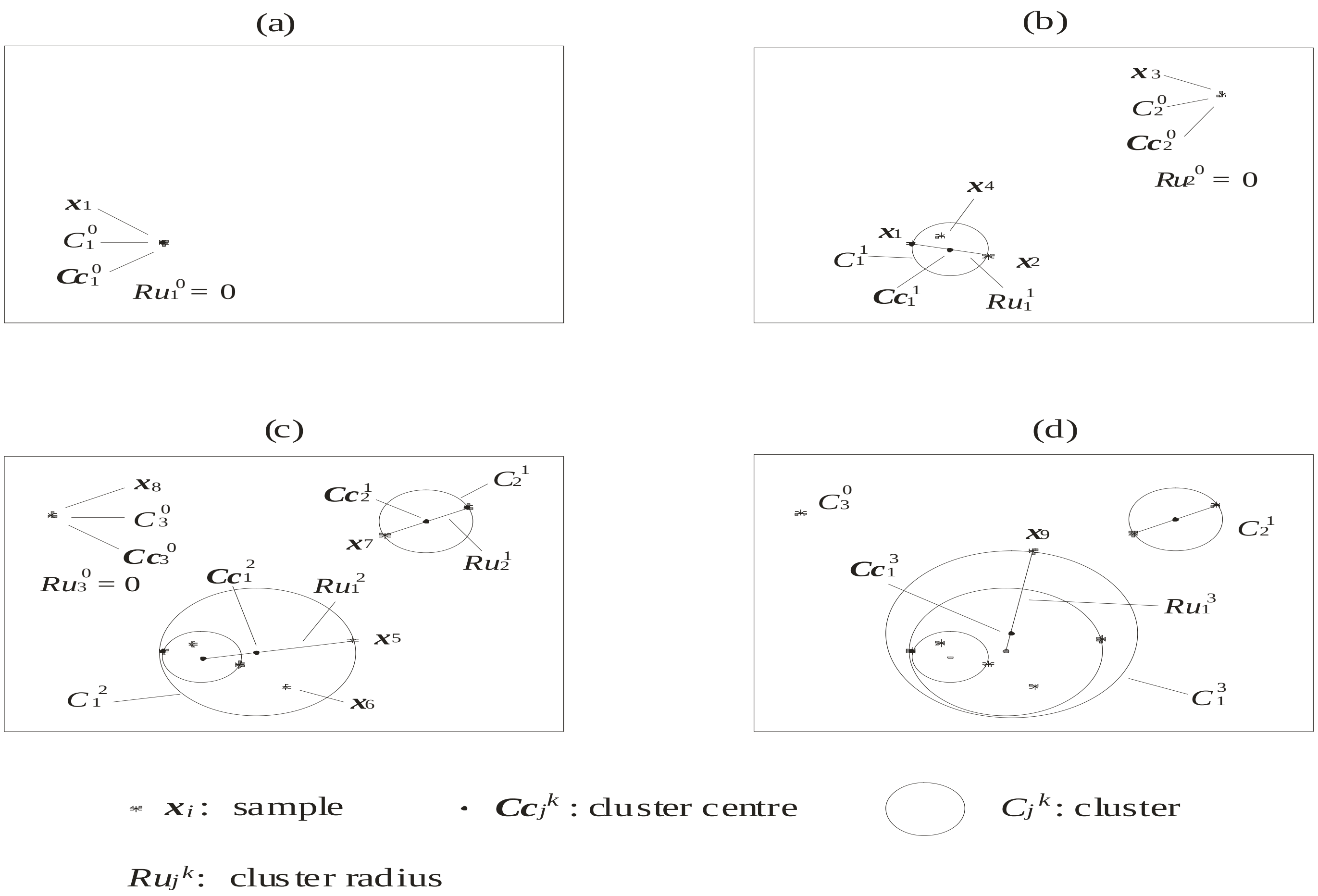
- Early ECOS models: RAN (J.Platt, 1991) – evolving RBF NN; Incremental FuzzyARTMAP (Carpenter , Grossberg); Growing gas; EFuNN (Kasabov, 1998, 2001); ESOM (Deng and Kasabov, 2002); DENFIS (Kasabov, Song, 2002); EFuRS, eTS (Angelov, 2002;Filev, 2002).

- M.Watts, *Ten years of Kasabov's evolving connectionist systems, IEEE Tr SMC- part B, 2008.*

- New developments: Ensembles of EFuNNs (T. Ljudemir, 2008-); Application oriented ECOS (B.Gabric, R.Duro, McGinitty et al.); Incremental feature selection (Ozawa, Pang, Kasabov, Polikar, Minhu Lee); evolving spiking neural networks (eSNN); computational neuro-genetic systems; quantum inspired eSNN.

Evolving clustering methods

- No predefined clusters
- Clusters are created from incoming data
- Centre and Radius of a cluster are evolving



Evolving Fuzzy Neural Network (EFuNN)

- Incremental, supervised clustering

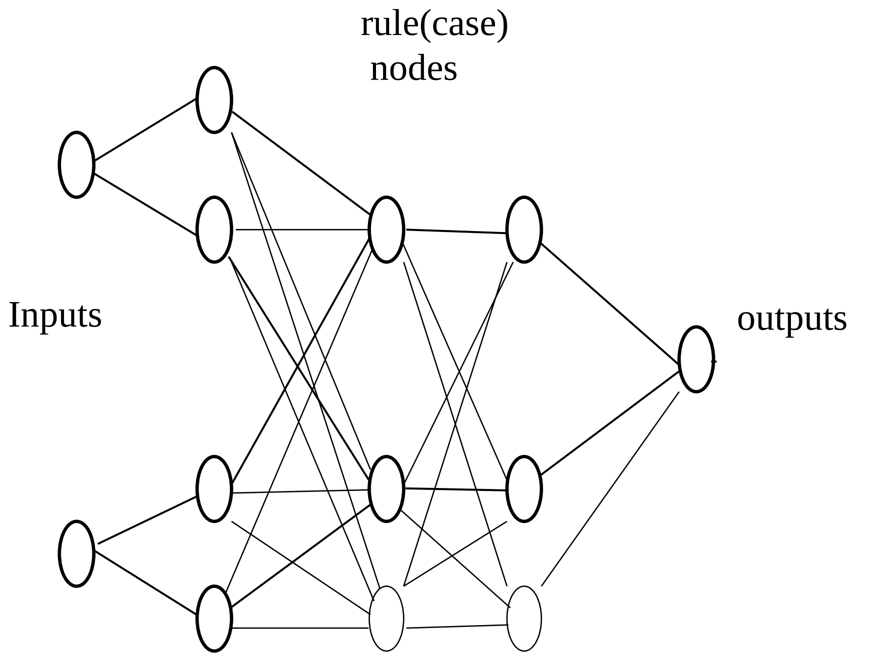
- Input and/or output variables can be non-fuzzy (crisp) or fuzzy

- Hidden nodes evolve to capture clusters (prototypes) of input vectors

- Input weights change based on *Euclidean distance* between input vectors and prototype nodes (evolving clustering):

  $\Delta \mathbf{w} = \text{lrate} * E(\mathbf{x}, Rn)$

- Output weights evolve to capture local output function and change based on output error.

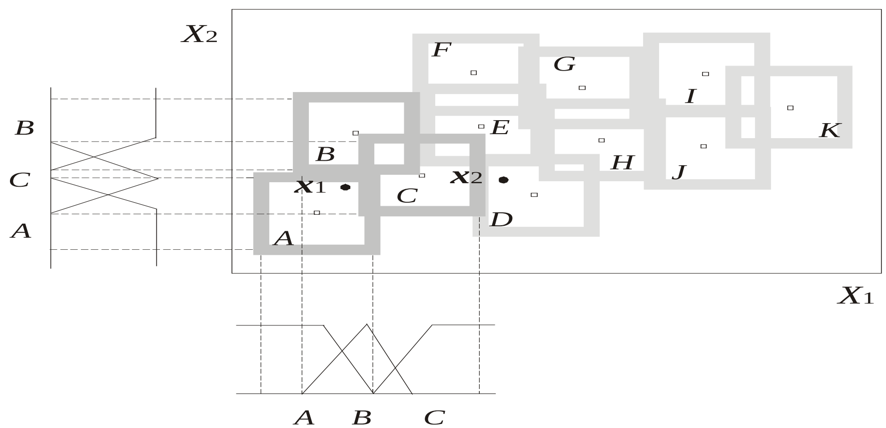


- EFuNN, N. Kasabov, IEEE Tr SMC, 2001
- DENFIS, N.Kasabov , Q.Song, IEEE Tr FS, 2002
- ECOS Toolbox available in MATLAB
- NeuCom Software available: www.kedri.info

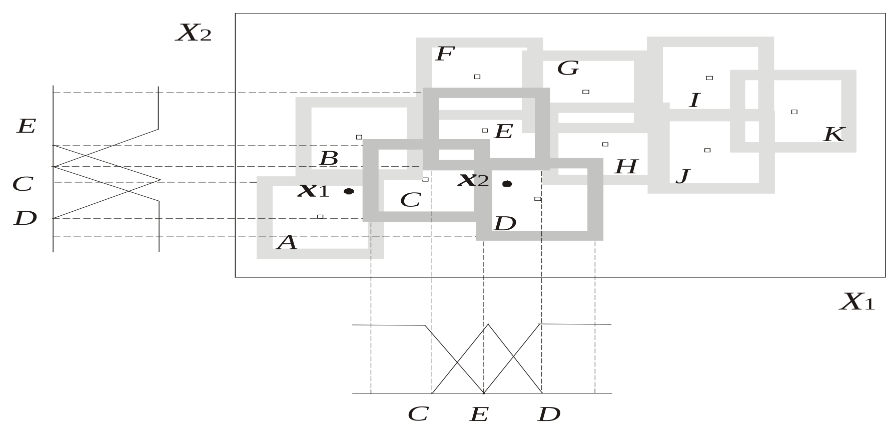
DENFIS: Evolving Neuro-Fuzzy Inference System

(DENFIS, Kasabov and Song, 2002, IEEE Tr Fuzzy Systems)

(a) Fuzzy rule group 1 for a DENFIS



(b) Fuzzy rule group 2 for a DENFIS



DENFIS algorithm:

(1) Learning:

- Unsupervised, incremental clustering.
- For each cluster there is a Takagi-Sugeno fuzzy rule created: IF x is in cluster Cj THEN yj = fj (x),

where: yi = β0 + β1 x1 + β2 x2 + … + βq

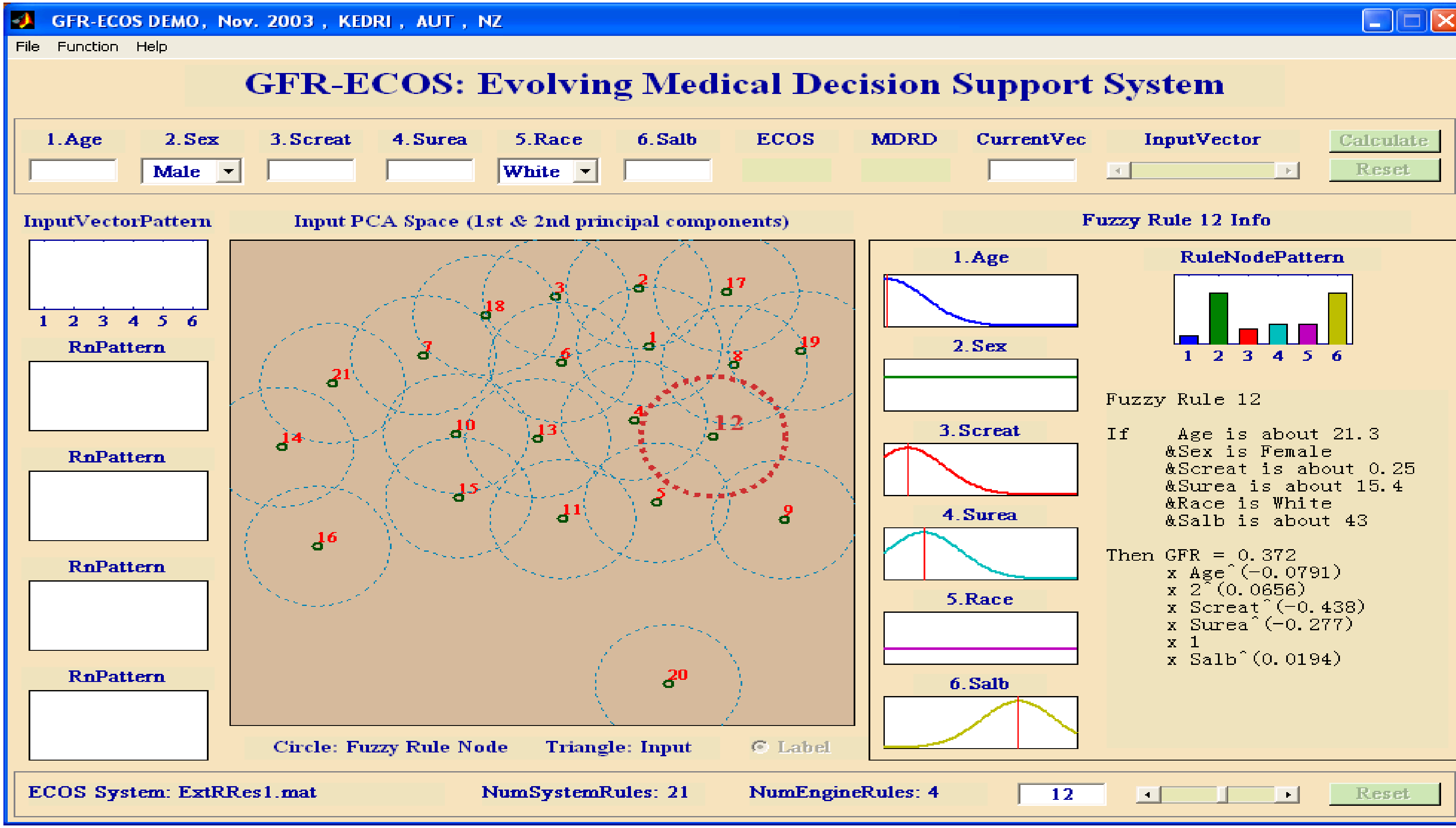
- Incremental learning of the function coefficients and weights of the functions through least square error

(2) Fuzzy inference over fuzzy rules:

- For a new input vector x = [x1,x2, … , xq] DENFIS chooses m fuzzy rules from the whole fuzzy rule set for forming a current inference system.
- The inference result is:

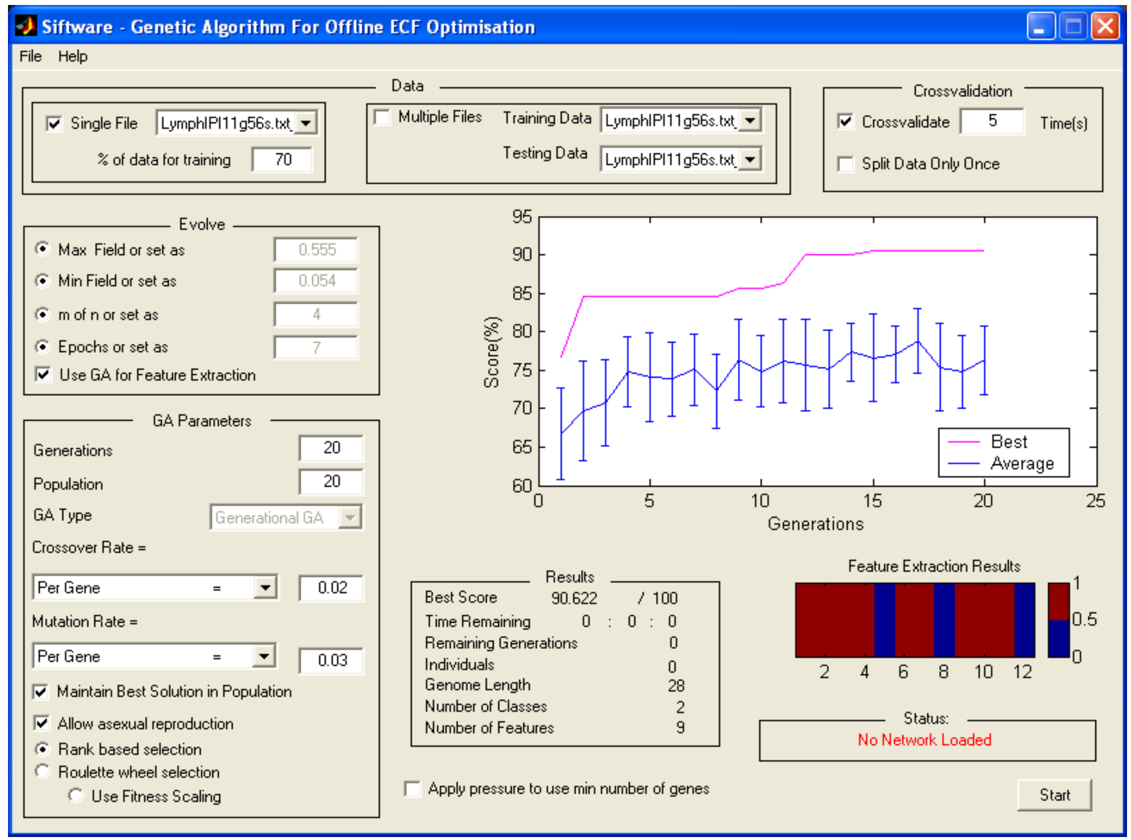
$$y = \frac{\Sigma_{i=1,m} \; [\, \omega i \; fi\,(\, x1, x2, \ldots, xq \,)]}{\Sigma_{i=1,m} \; \omega i}$$

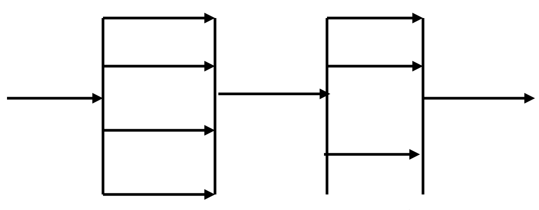
Example: Locally adaptive decision support system based on DENFIS



Evolutionary Computation (EC) for feature-, parameter-, and structure optimisation of ECOS

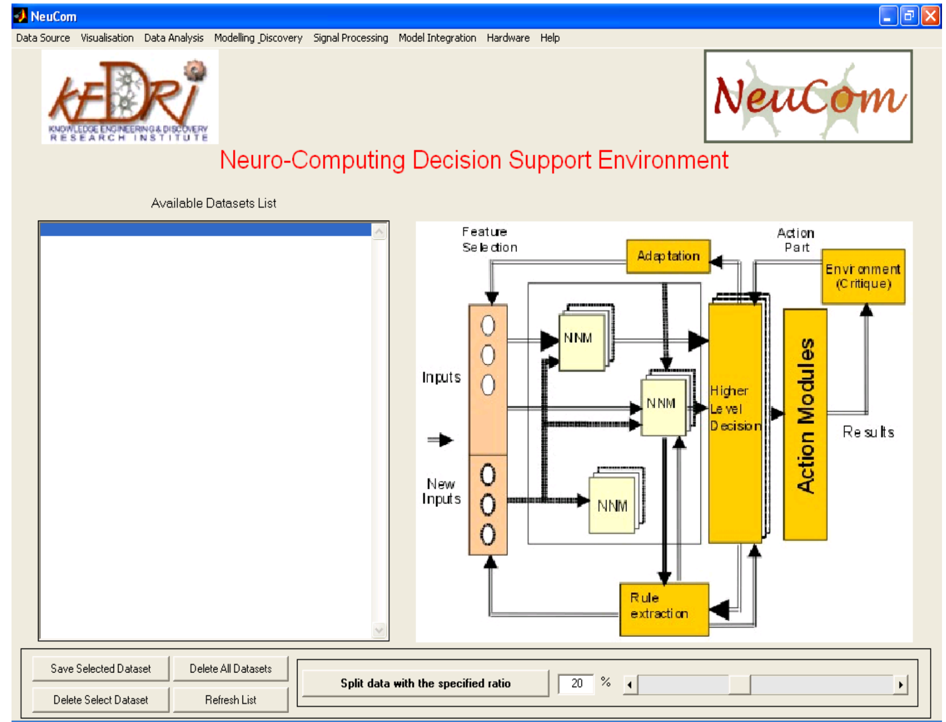
- GA optimisation of the parameters of the model and the input features
- A chromosome contains as "genes" all model parameters and input features (yes, no)
- Replication of individual models and selection of:
  - The best one
  - The best *m* averaged, etc





NeuCom: A Software Environment for NeuroComputing, Data Mining and Intelligent System Design (www.theneucom.com)

- A generic environment, that incorporates 60 traditional and new techniques for intelligent data analysis and the creation of intelligent systems, including:
  - Statistical methods
  - Neural networks



- Methods for feature selection
- Methods for classification
- Methods for prediction
- Methods for knowledge extraction
- Fast data analysis and visualisation
- Fast model prototyping
- A free copy available for education and research from: www.theneucom.com
- DENFIS for prediction
- ECF for classification

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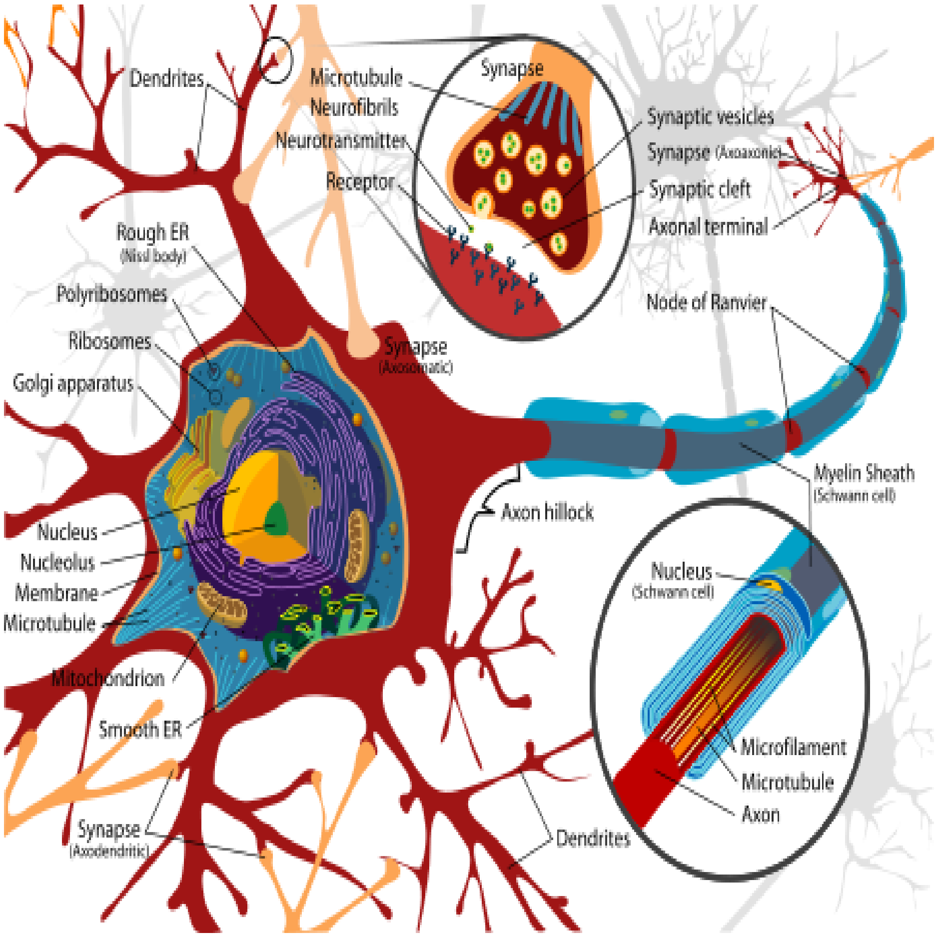
3. Spiking Neural Networks (SNN) and eSNN



Brain-like ANN

A single neuron is very rich of information processes: time; frequency; phase; field potentials; molecular (genetic) information; space.

Three, mutually interacting, memory types

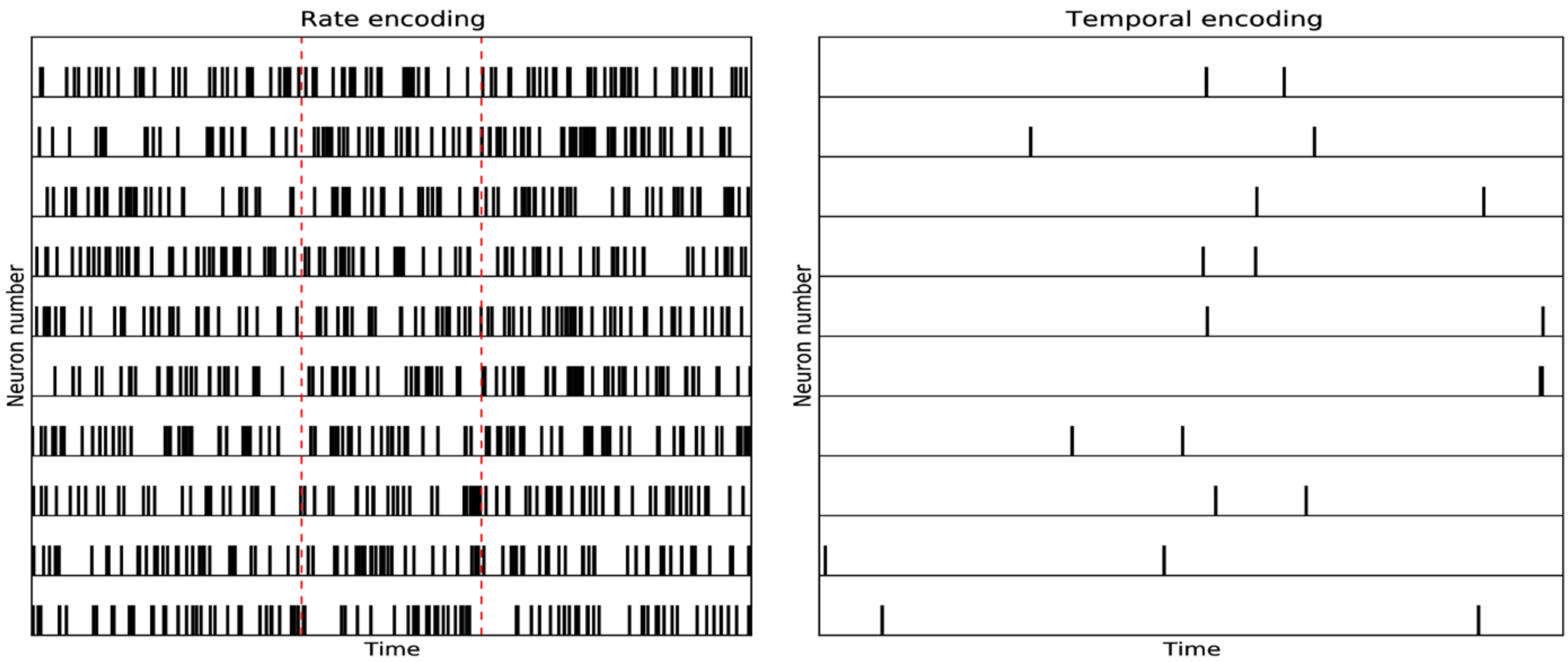
- short term;
- long term
- genetic

SNN can accommodate both spatial and temporal information as location of neurons/synapses and their spiking activity over time.

Encoding information as spikes: Rate vs time-based

- Rate-based coding: A spiking characteristic within a time interval, e.g. frequency.

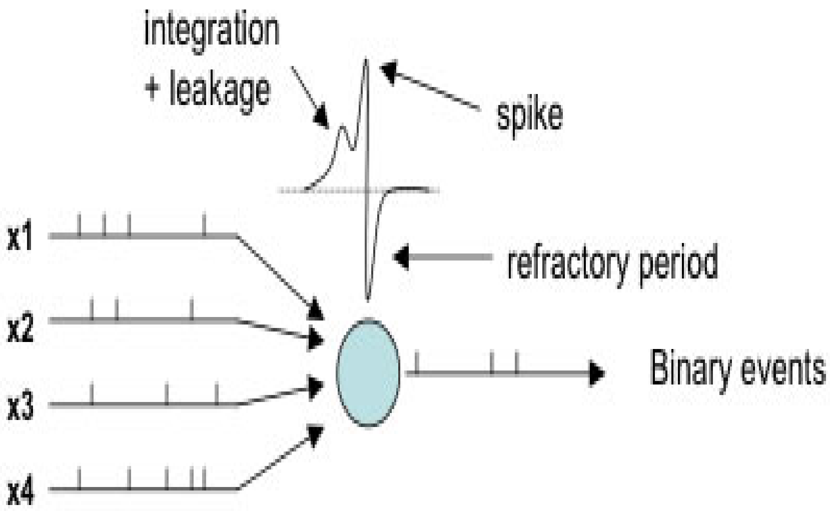
- Time-based (temporal) coding: Information is encoded in the time of spikes. Every spike matters! For example: class A is a spike at time 10 ms, class B is a spike at time 20 ms.



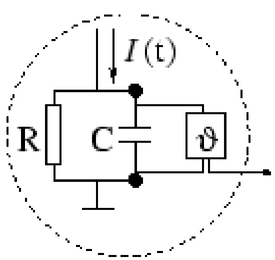
Models of spiking neurons:

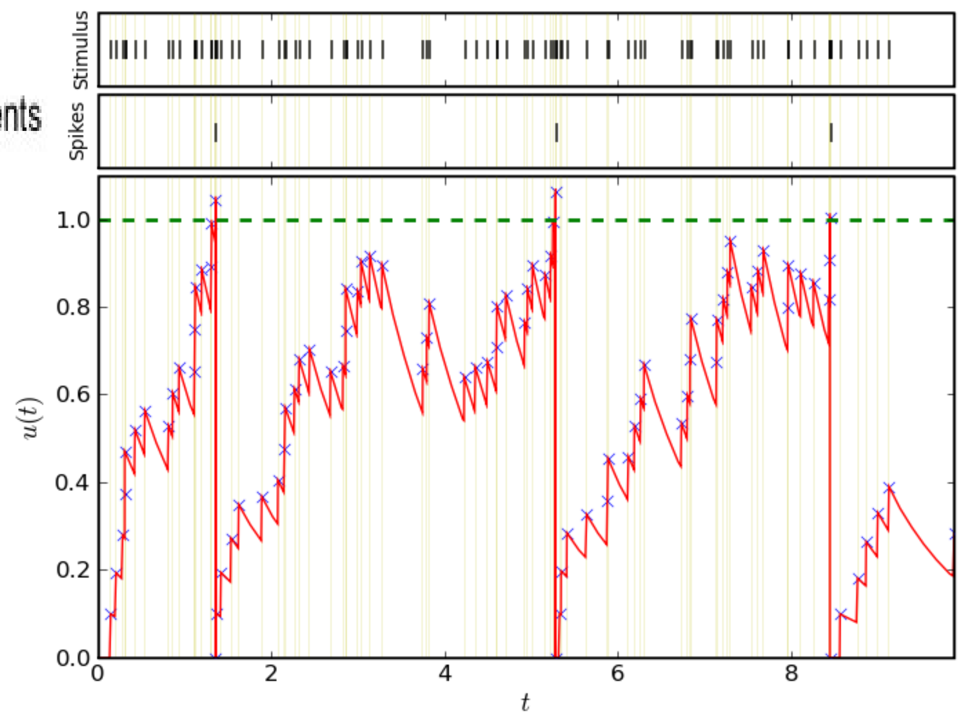
(Hodgkin-Huxley 1952; Abbott, 2000; Maas, Izhikevich; other)

Most popular is the Leaky Integrate and Fire Model (LIF) .



$$\tau_m \frac{du}{dt} = -u(t) + RI(t)$$





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Evolving SNN – eSNN

- eSNN: Creating and merging neurons based on localised information (Kasabov, 2007; Wysoski, Benuskova and Kasabov, 2006-2009)
- Uses the first spike principle (Thorpe et al.) for fast on-line training
- For each input vector

  a) Create (evolve) a new output spiking neuron and its connections

  b) Propagate the input vector into the network and train the newly created neuron

$$u_i(t) = \begin{cases} 0 & \text{if fired} \\ \sum_{j|f(j)<t} w_{ji} m_i^{\mathrm{order}(j)} & \text{else} \end{cases}$$

$$\Delta w_{ji} = m^{\mathrm{order}(j)}$$

Weights change based on the spike time arrival

  c) Calculate the similarity between weight vectors of newly created neuron and existing neurons: IF similarity > Threshold THEN Merge newly created neuron with the most similar neuron

$$W \Leftarrow \frac{W_{new} + NW}{1+N}$$

where N is the number of samples previously used to update the respective neuron.

  d) Update the corresponding threshold ϑ:

$$\vartheta \Leftarrow \frac{\vartheta_{new} + N\vartheta}{1+N}$$

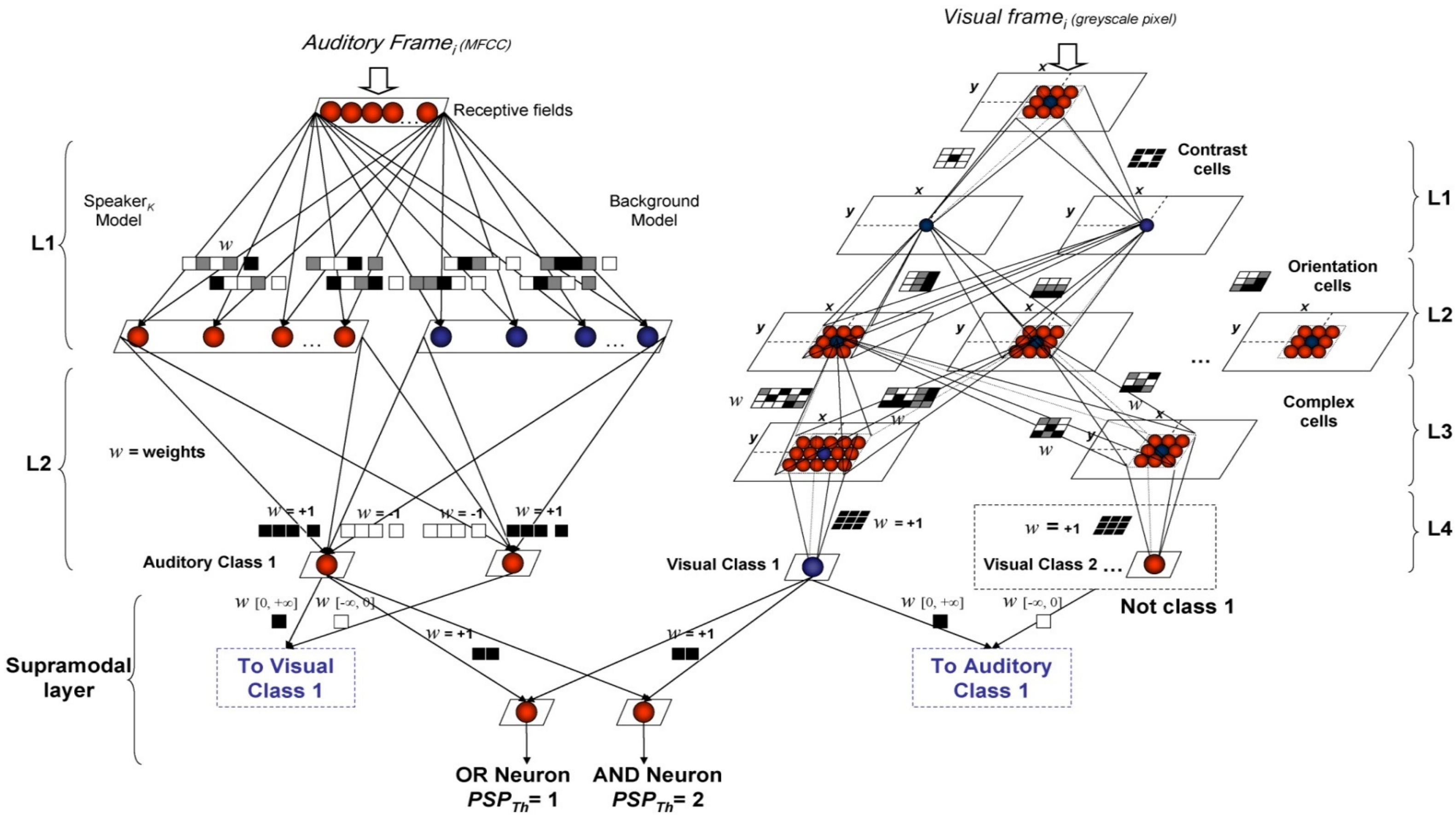
- Schliebs, S. and N.Kasabov, Evolving spiking neural networks: A Survey, *Evolving Systems*, Springer, 2013.

eSNN evolve new output neurons to learn new input patterns through *one-pass* RO learning.

Merging can be applied based on Euclidean distance

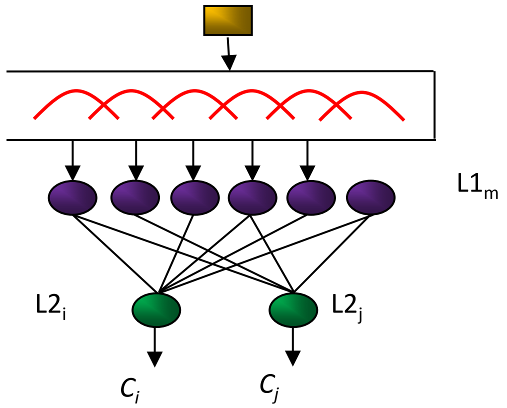
Example: Person authentication based on speech and face data

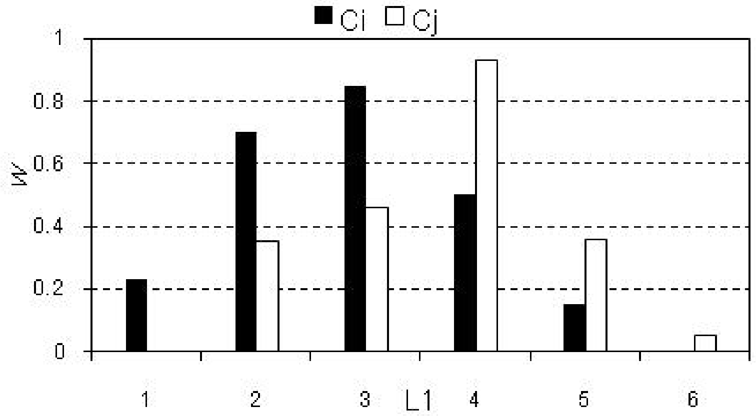
(Wysoski, Benuskova and Kasabov, *Neural Networks*, 2010)



Methods for fuzzy rule extraction from eSNN

(S.Soltic, N.Kasabov, Int. J. Neural Systems, World Sc. Publ., 2010)

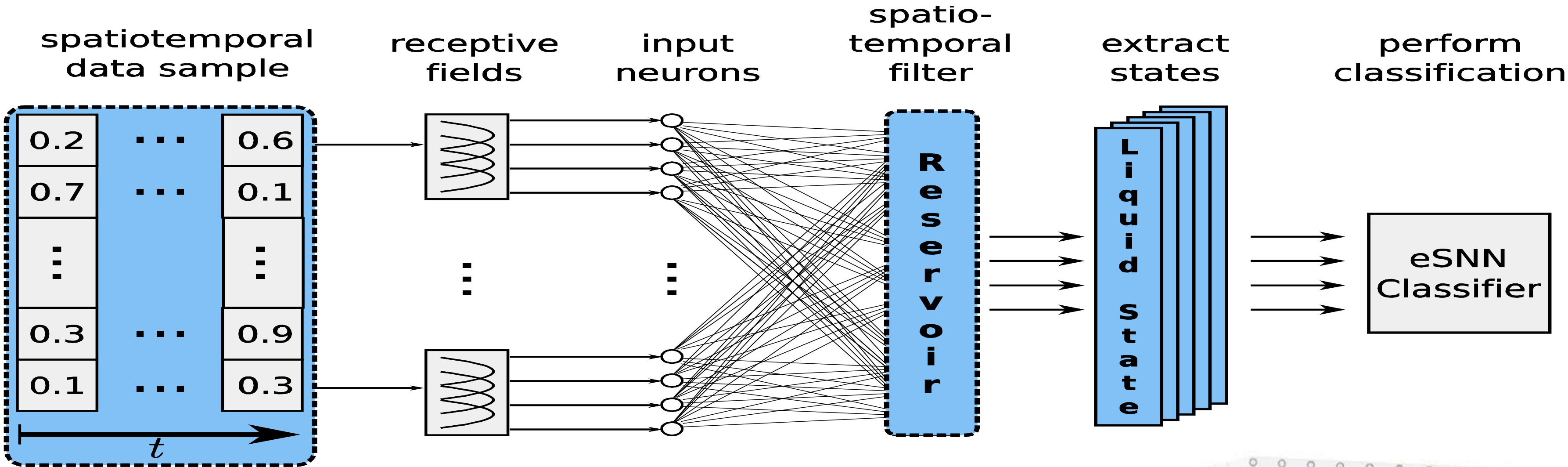


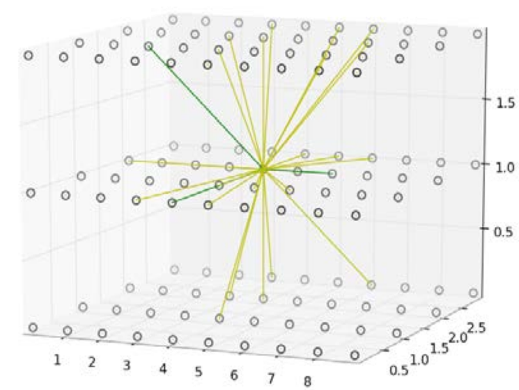


$$IF \quad v \text{ is } SMALL \quad THEN \ C_i$$

$$IF \quad v \text{ is } LARGE \quad THEN \ C_j$$

Reservoir-based eSNN



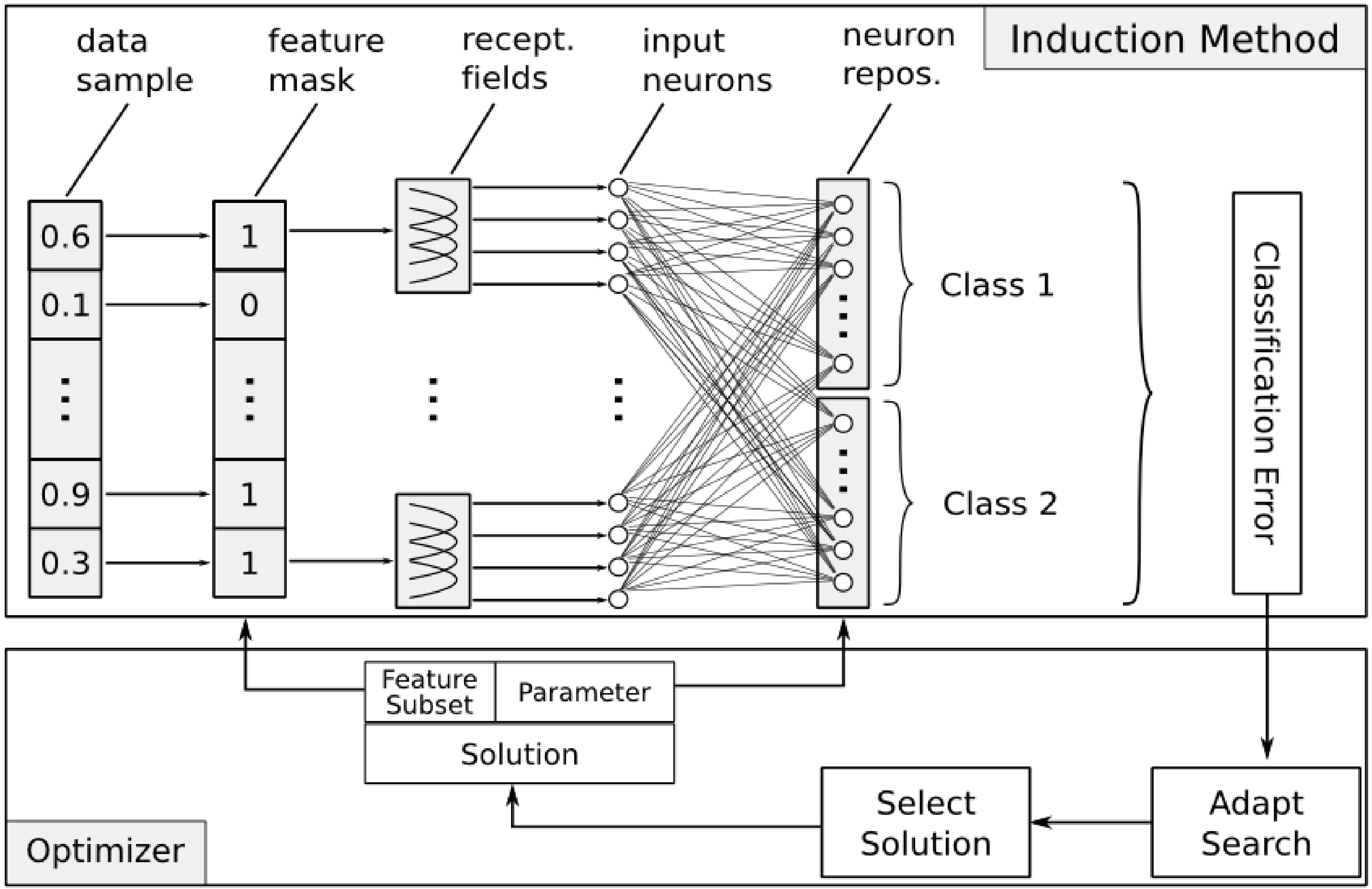


- *Maass, W., Natschl ̈ager, T., Markram, H.: Real-time computing without stable states, Neur. Comp. 14(11),2002;*
- Input (feature) neurons connected to part of the LSM
- Output neurons connected to part of the LSM
- LSM recurrent connections, e.g. small world connections
- Excitatory 80%, Inhibitory 20%
- Learning in LSM: STDP; spike time delay ....???
- Polychronization (Izhikevich): ‘opening the box’?

$$p_{a,b} = C \times e^{-D^2_{a,b}/\lambda^2}$$

Quantum-inspired EC for the optimisation of eSNN

(Kasabov, 2007-2008; S.Schliebs, M.Defoin-Platel and N.Kasabov, 2008)



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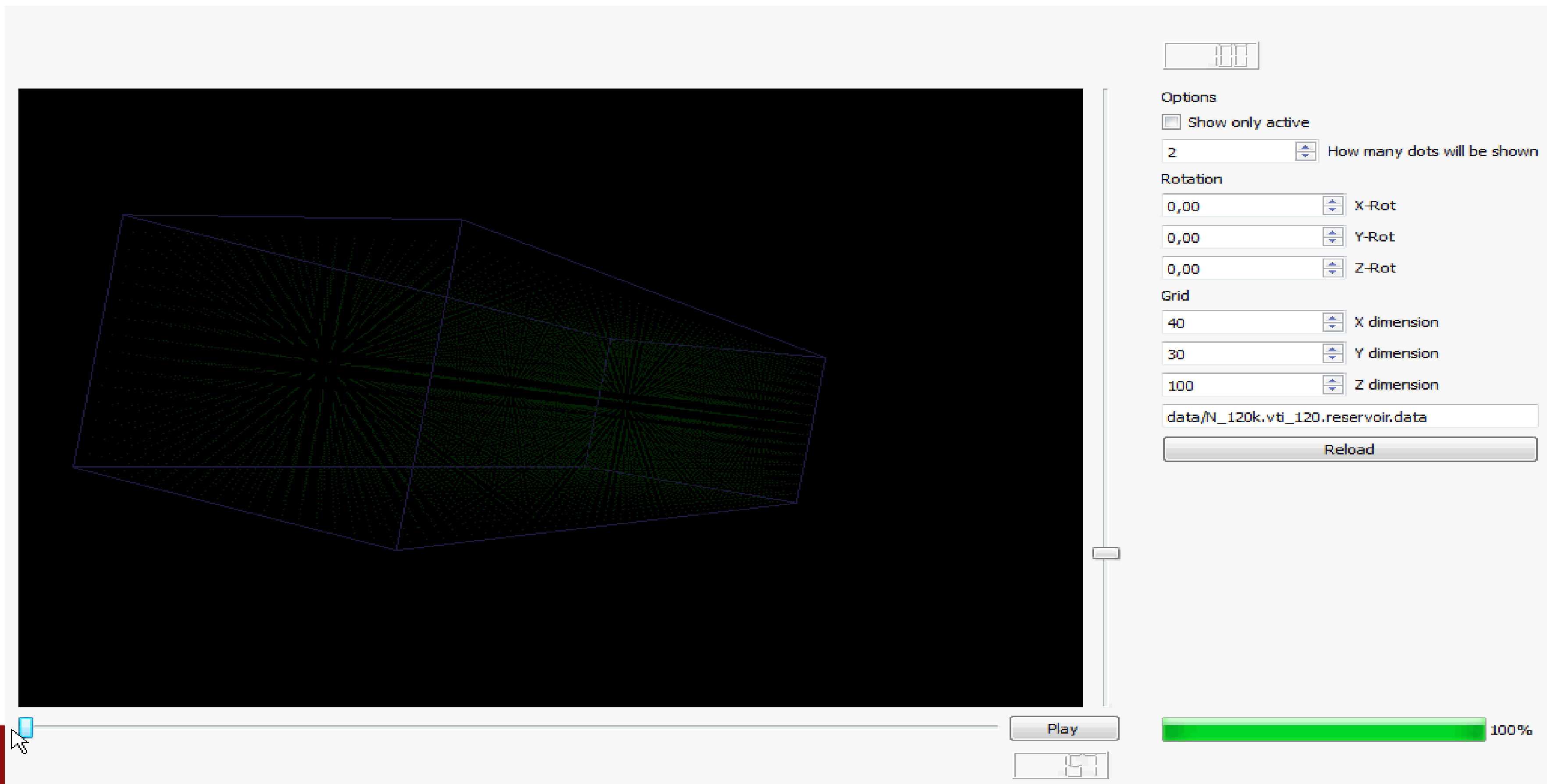
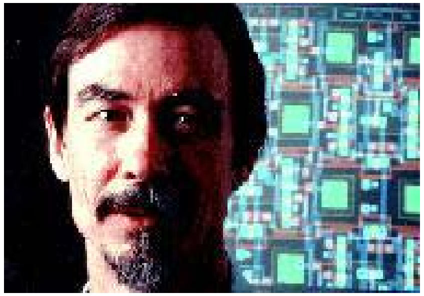
The EvoSpike Simulator

A collection of modules and functions written in Python using functions from Brian library:
- Converting continuous-value input data into spike trains;
- SNN for spatio-temporal pattern recognition (SPAN, deSNN, LSM deSNN, …);
- Knowledge extraction from trained eSNN;
- Presenting results and visualisation of learning processes ;
- Connecting software modules with neuromorphic hardware.



Progress in neuromorphic computation



Hodgin- Huxley model (1952)

Carver Mead (1989): A hardware model of an IF neuron:
The Axon-Hillock circuit;

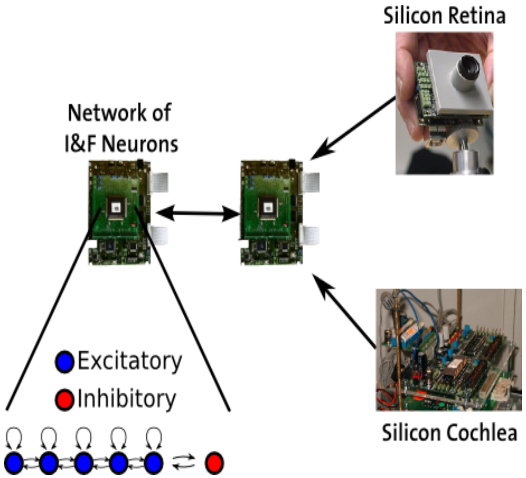
INI Zurich SNN chips (Giacomo Indivery, 2008 and 2012)

FPGA SNN realisations (McGinnity, Ulster, 2010);

The IBM chip (D.Modha, 2012): 256 LIF neurons and 64k synapses in a chip.

U. Manchester SpiNNaker (2^{16} computer chips, 2011; 1 mln neurons 2013)

Stanford U., NeuroGrid (Kwabena Boahen et al), 1mln neurons on a board, 63 bln connections ; hybrid - analogue /digital)

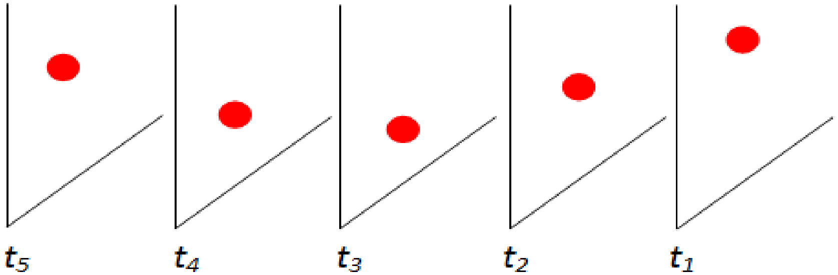


The challenge: Technology is available, but how do we use it for engineering applications?

4. Applications for Spatio/Spectro-temporal Pattern Recognition

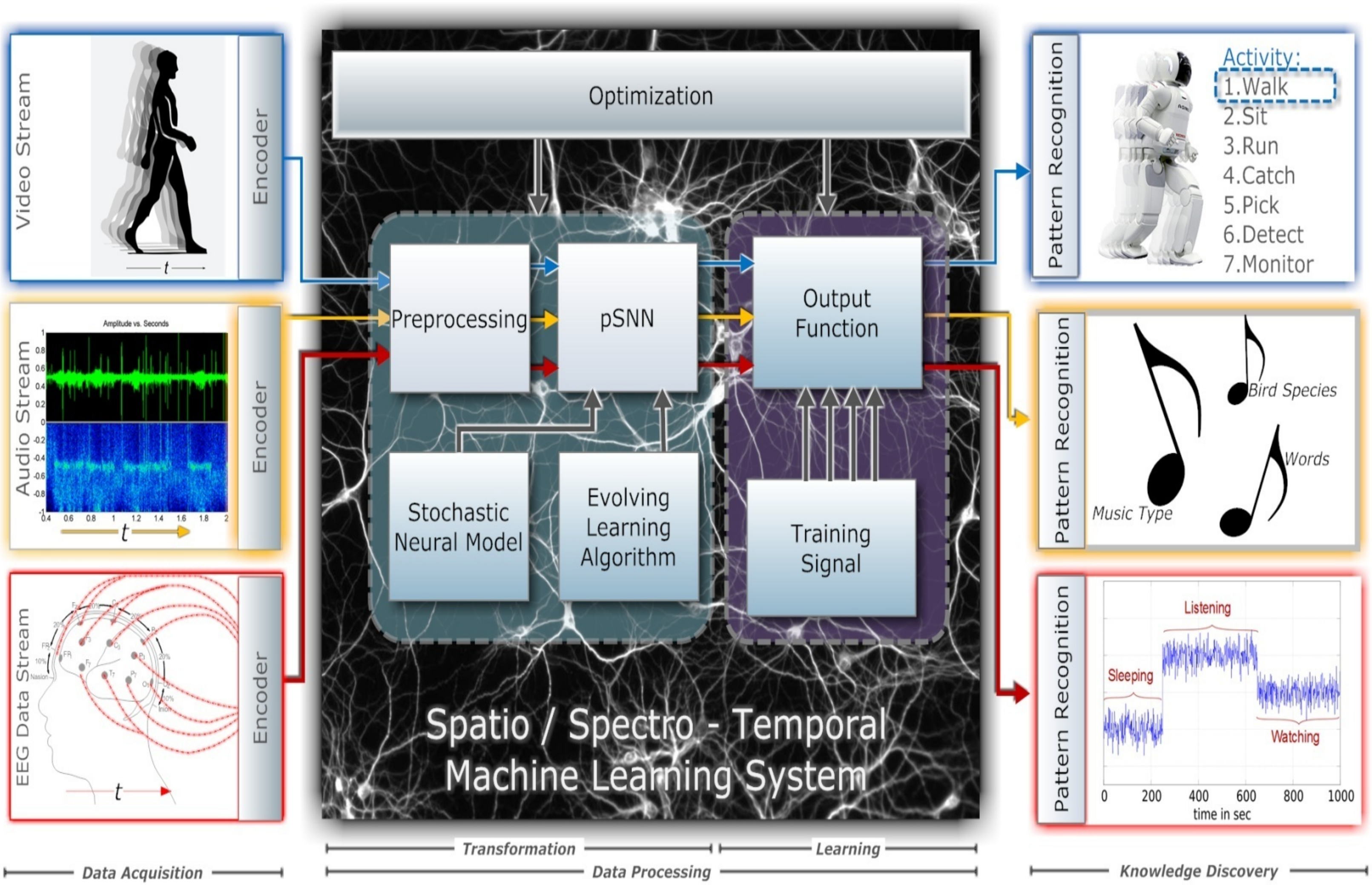
- Most real world data is spatio- or spectro- temporal.
- In STPR problems spatial and temporal components of the information are interrelated.
- Examples of spatio-temporal data and related problems are:
  a) Object movement recognition from video data
  b) Audio/video data modelling
  c) Brain signals (EEG, MEG, fMRI)
  d) Brain- computer interfaces
  e) Motor control for prosthetics
  f) Ecological and environmental data, e.g. earthquake prediction
  g) Robot control
  h) Cyber-security data

- Goal: Developing new methods based on ECOS and eSNN for STPR



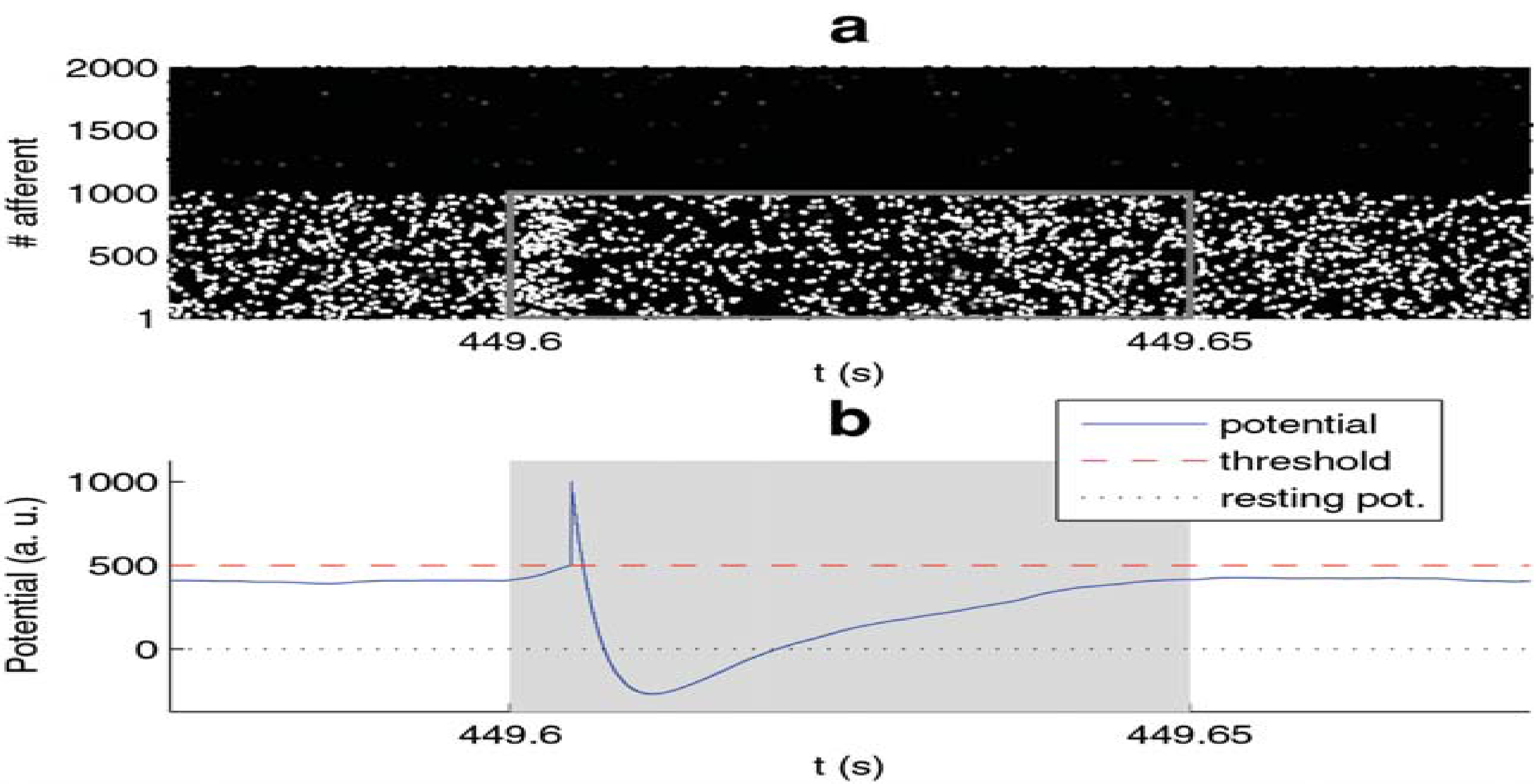
Spatio-temporal input data

The EvoSpike Project: EU FP7Marie Curie (http://ncs.ethz.ch/projects/evospike)



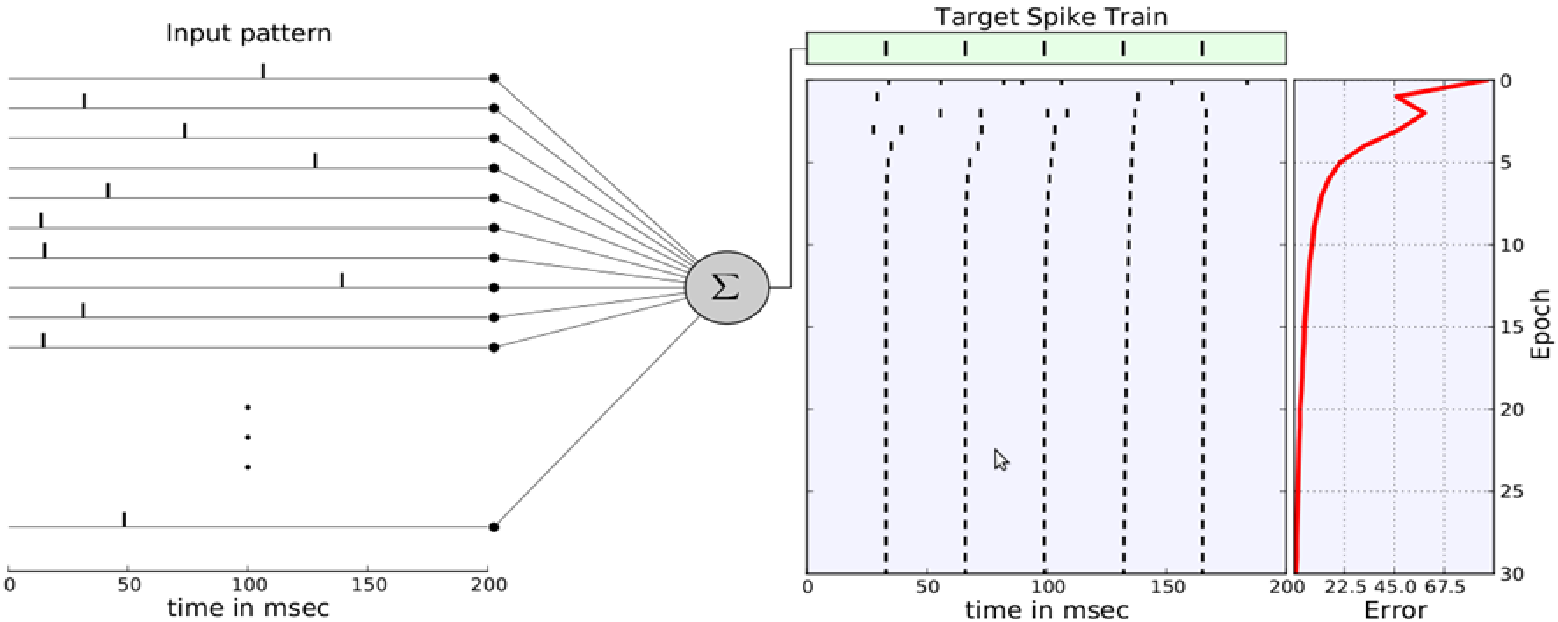
What can a single spiking neuron do in terms of STPR?

A single LIF neuron with simple synapses can be trained with the STDP unsupervised rule to discriminate a repeating pattern of synchronised spike trains of thousands inputs from noise (T. Masquelier, R. Guyonneau and S. Thorpe, PlosONE, Jan2008))



SPAN: Spike Pattern Association Neuron and the Delta Rule

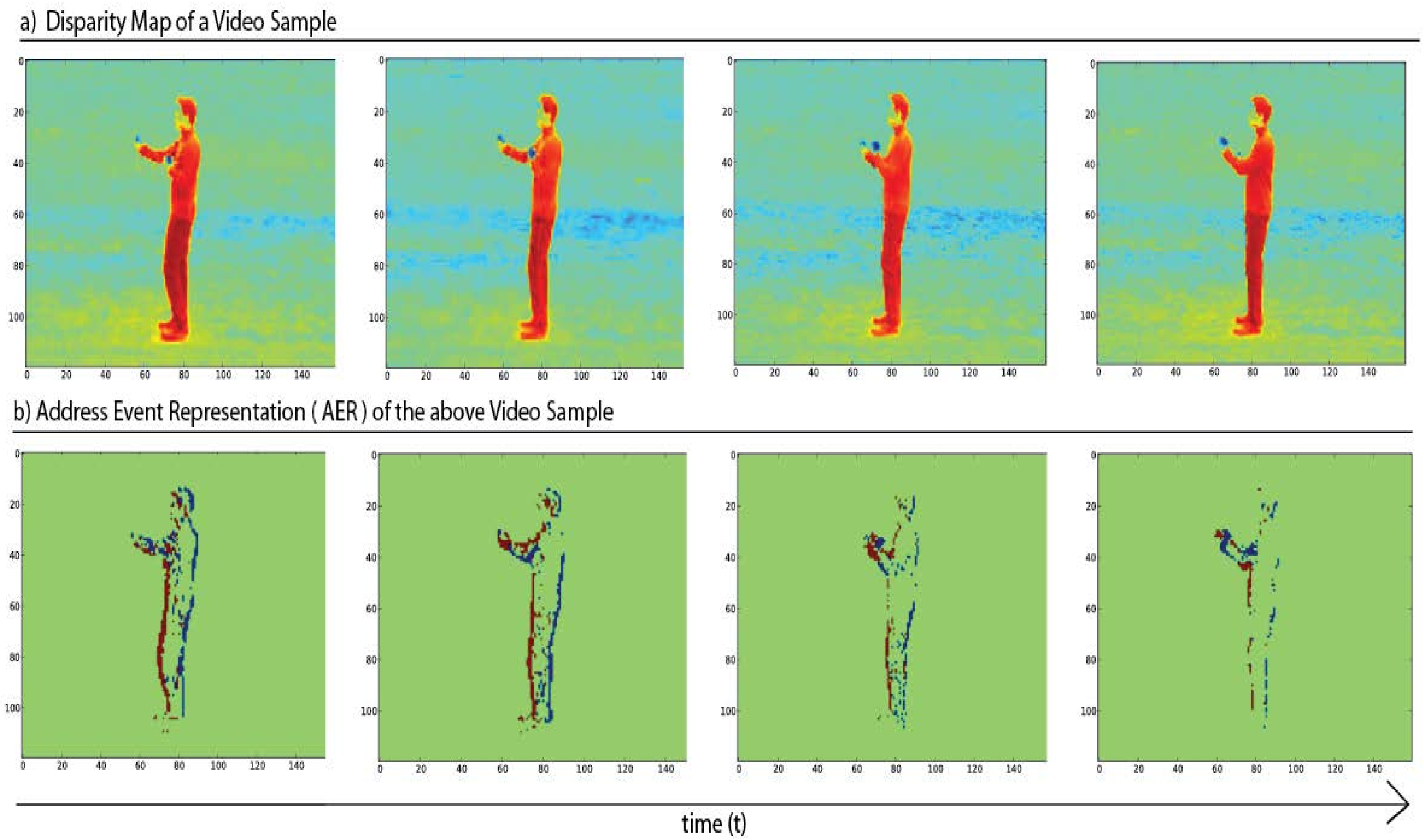
(A.Mohhemed et al, EANN 2011, ICONIP2011, IJNS, 2012; Neurocomputing, 2012))



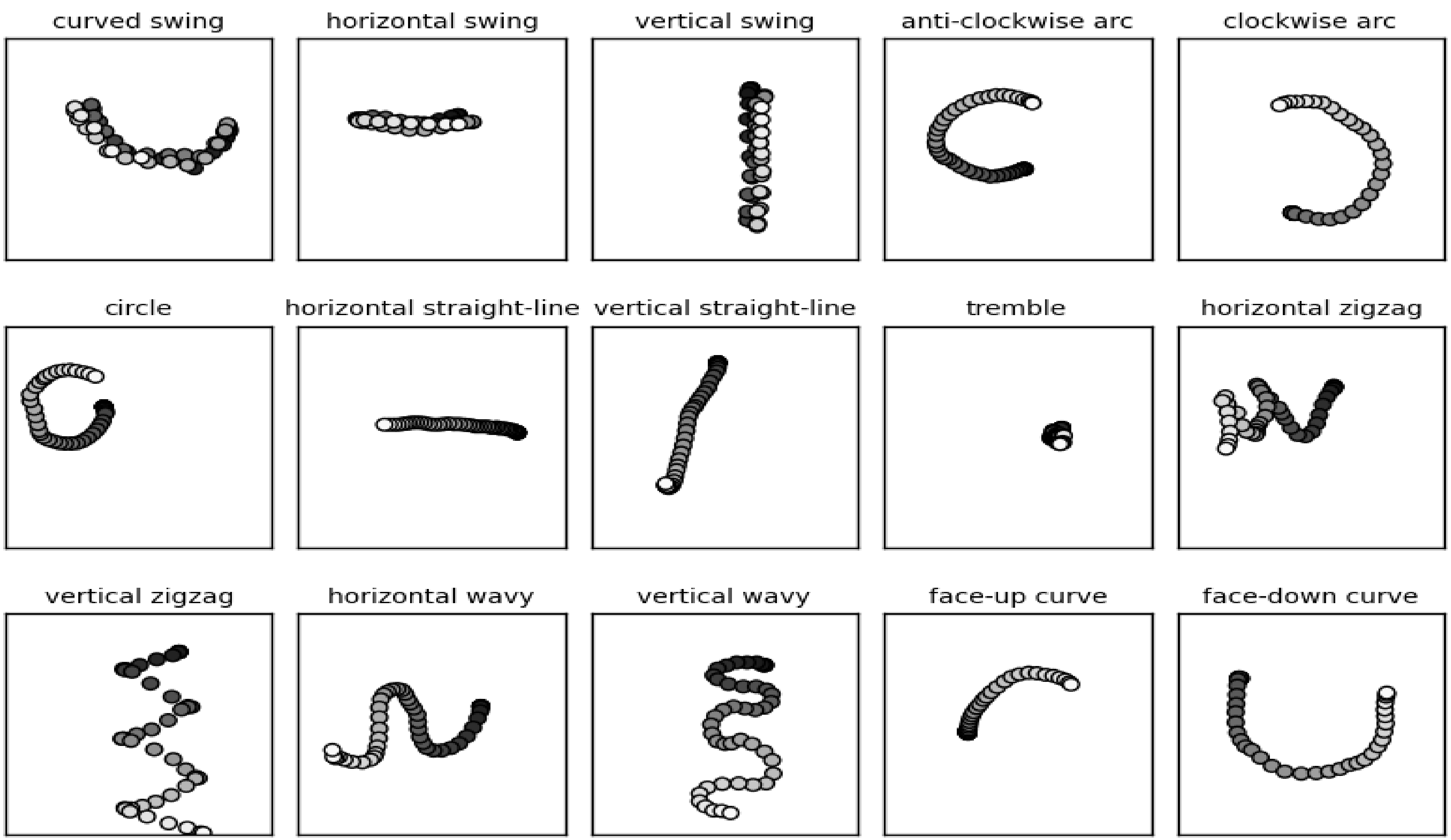
A single output neuron is trained to respond with a temporally precise output spike train to a specific spatio-temporal input.

Spike pattern association neuronal models: SpikeProp; ReSuMe; Tempotron; Chronotron.

Moving object recognition using AER and eSNN



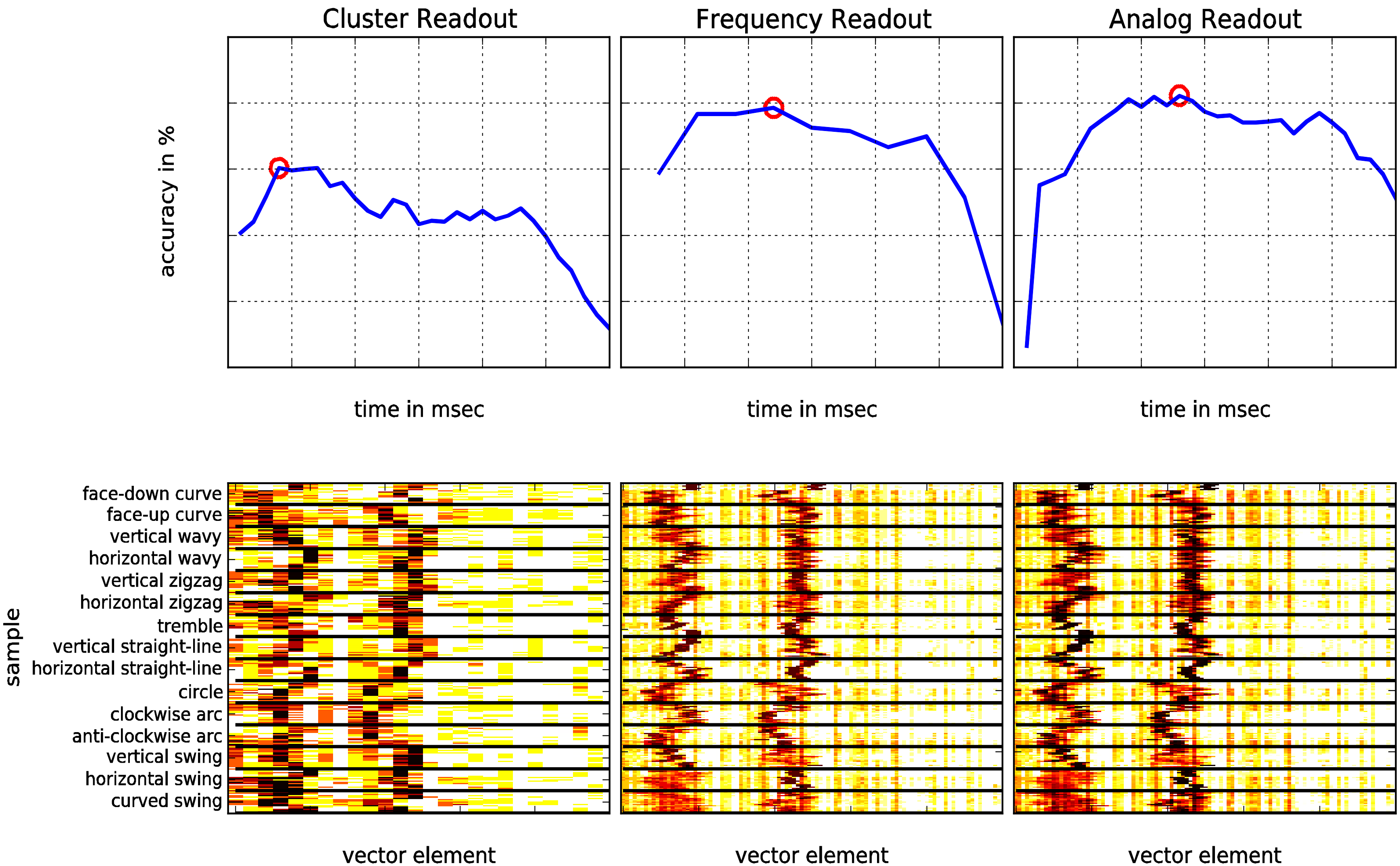
Brazilian Sign Language LIBRAS Pattern Recognition



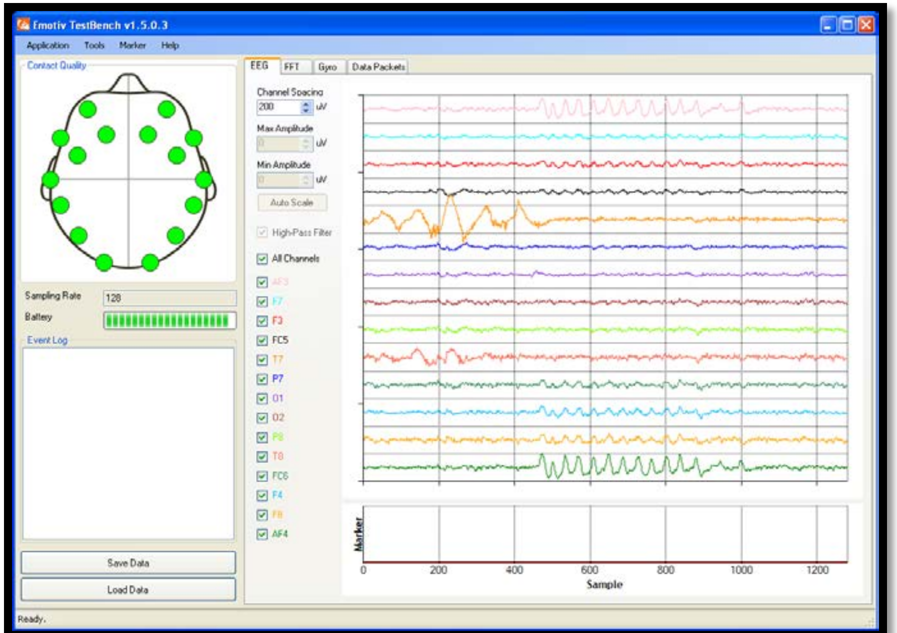
A single sample for each of the 15 classes is shown. The colour indicates the spatial position in 2D of a single point in time (black/white corresponds to earlier/later time points).

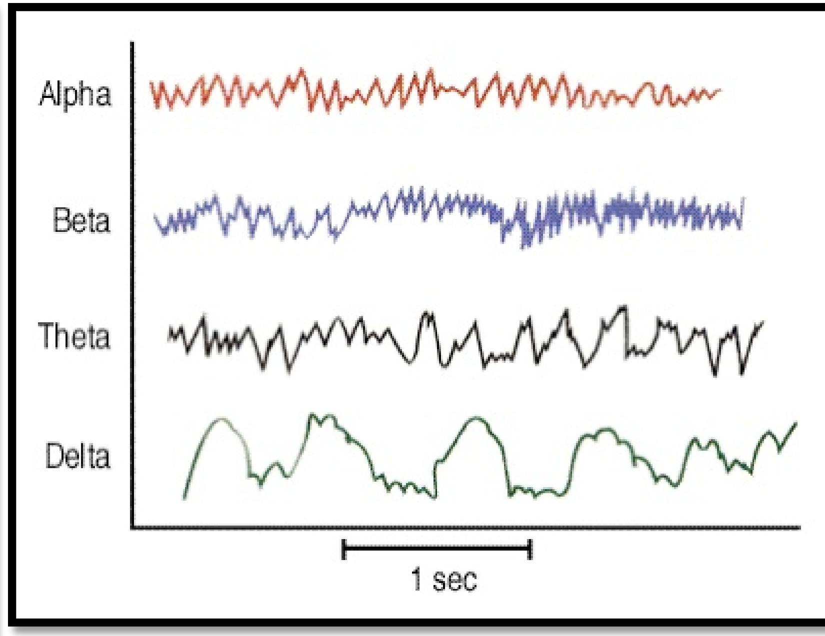
LIBRAS recognition with LSM reservoir and eSNN classifier using different methods to read the state of the LSM

(Schliebs, Nuzlu and Kasabov, ICONIP 2011)

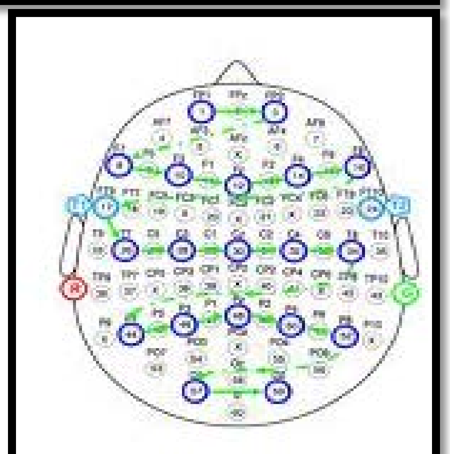


EEG STPR





(McFarland, Anderson, MÜller, Schlögl, Krusienski , 2006)



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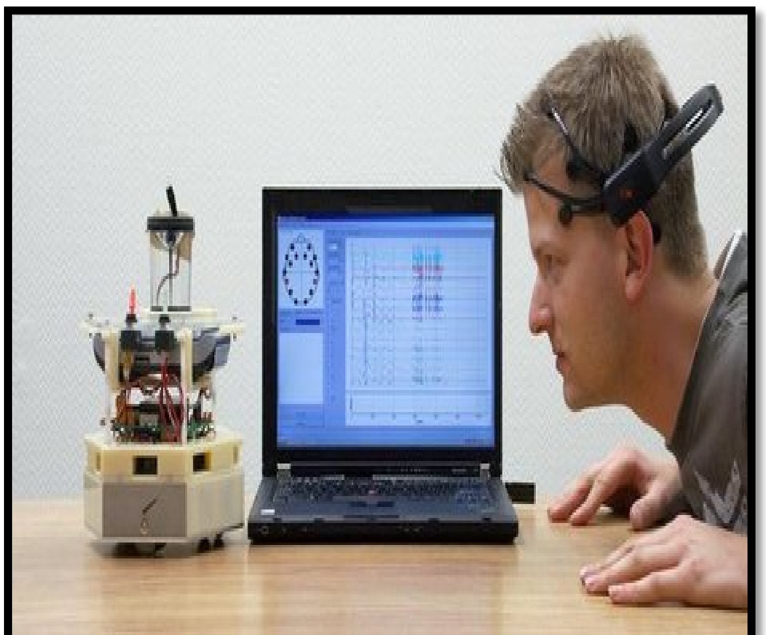
BCI

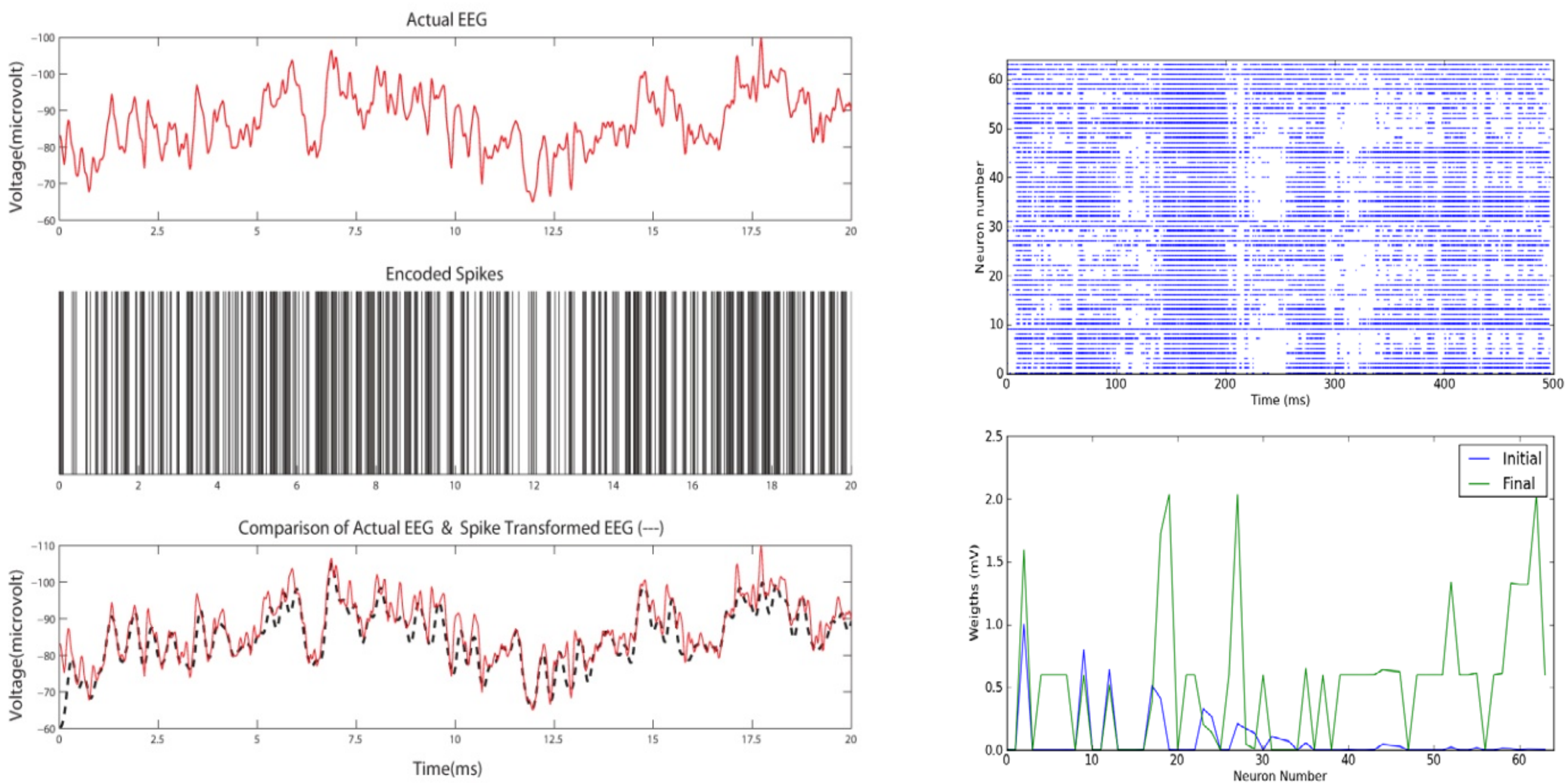
- Brain-Computer Interfaces (BCIs) are interfaces that allow humans to communicate directly with computers or external devices through their brains (e.g. EEG signals)
- Experiments with the WITH robot from KIT, prof. Yamakawa (S.Schliebs)
- Neuro-rehabiltation and neuro-prosthetics (with CAS, Z-G Hou)
- Collaborative work with U.Aveiro (P.Georgieva)



http://www.nzherald.co.nz

Example: STPR of brain EEG data in response to four stimuli

Data collected in RIKEN by van Leuwen: 64 channel EEG data of 500 msec is measured when four different stimuli are presented to one subject: image; sound; both, none.



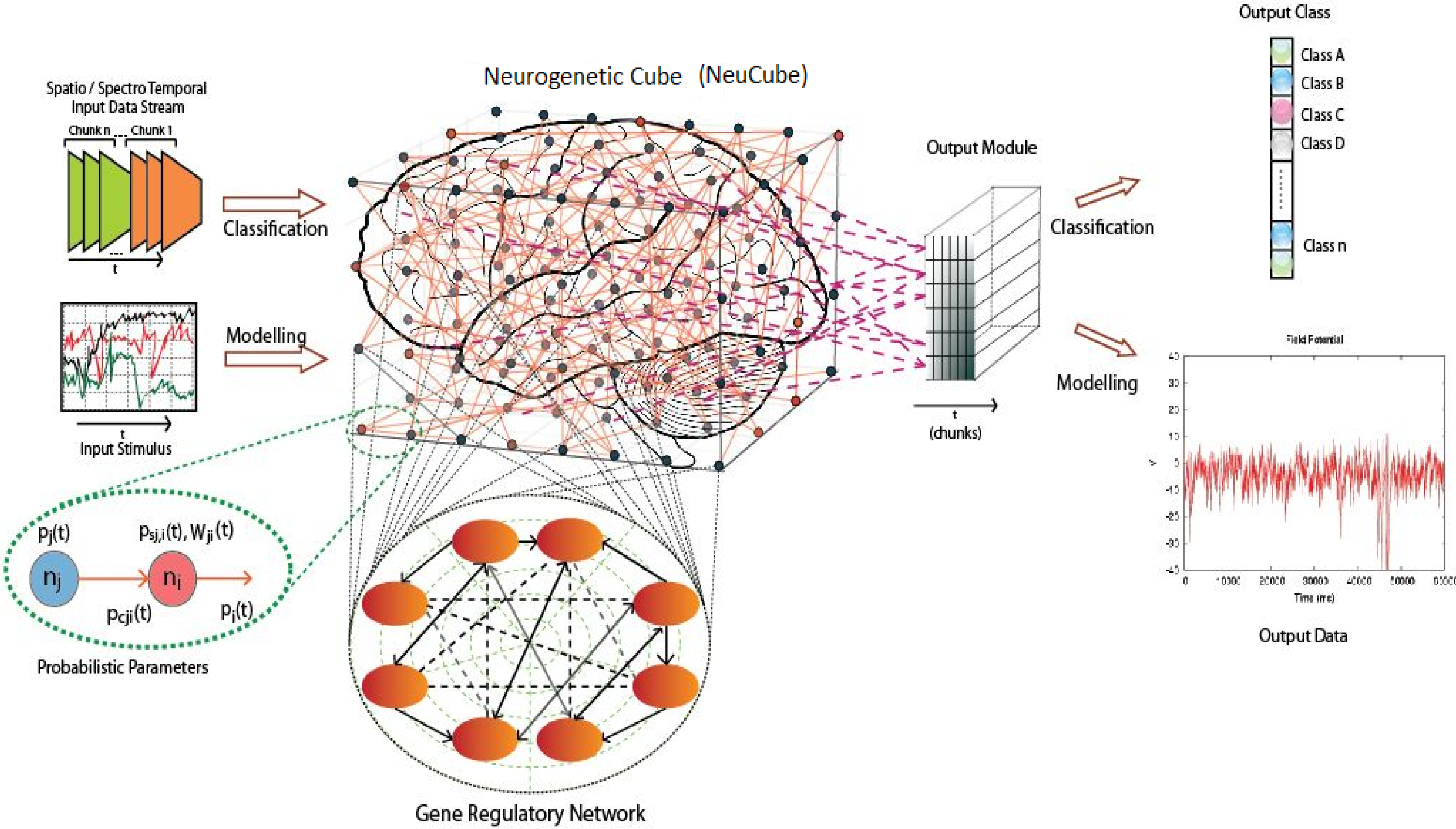
(a) Encoding EEG signals into spikes using the BSA (Ben's Spike Algorithm) by Schrauwen and van Campenhout, 2003 (N.Nuntalid and N.Kasabov, ICONIP2011)

(b) Exemplar spike trains on all 64 inputs for one EEG data sample (upper figure) and the weights changes of one output neuron (dedicated to this input sample) during the one pass presentation of the spike inputs to the DepSNNs model..

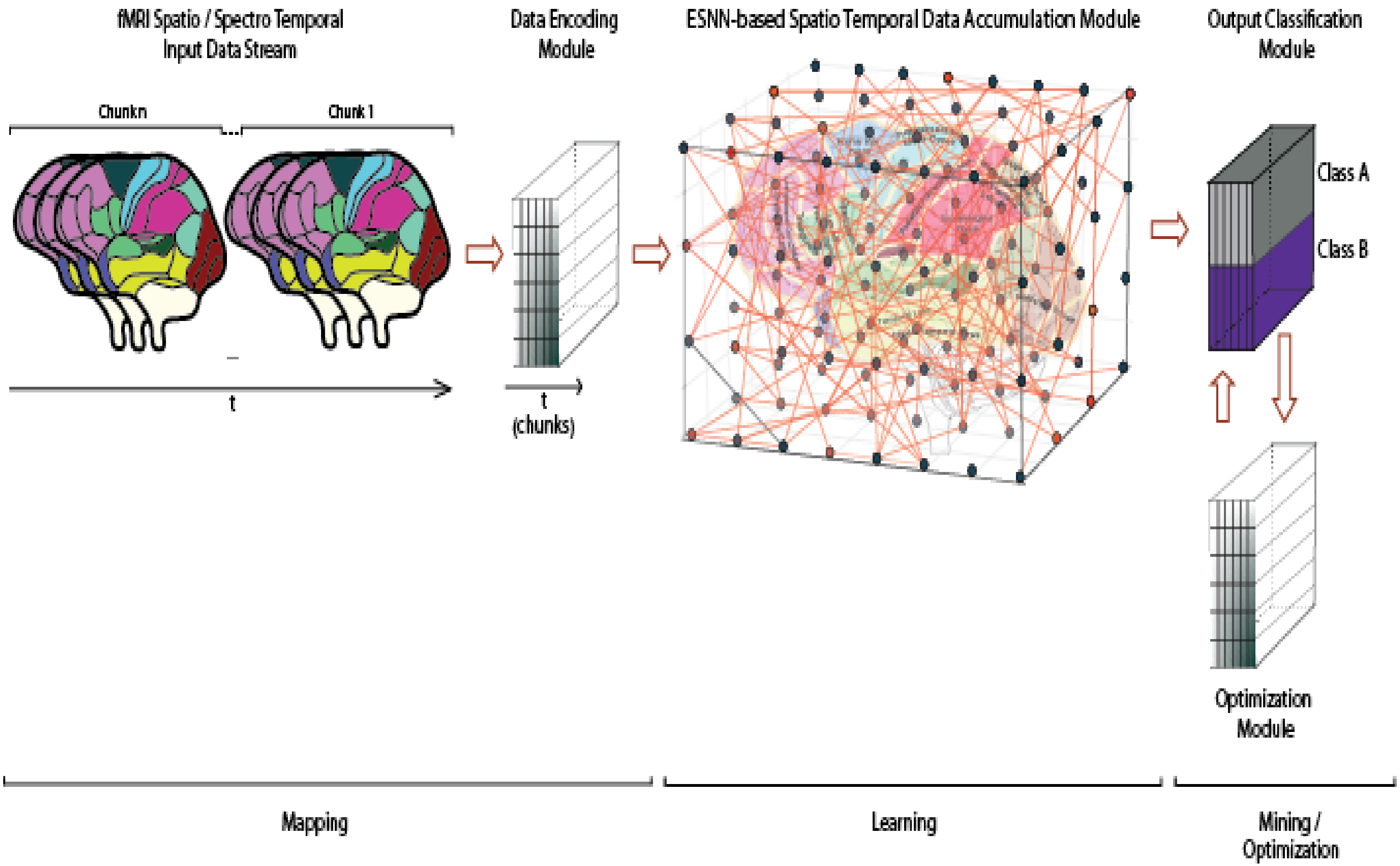
Results on the case study problem of EEG STPR

Classifier	Accuracy	Number of training iterations
MLP	64.87%	150
DepSNNs	**75%**	**1**

A NeuCube Framework and a Simulator for Brain Data Modelling and brain STPR
(Kasabov, Springer LNAI 7477, 2012)



NeuCube for fMRI STBD



Computational Neuro-Genetic Modelling (CNGM)

- SNN that incorporate a gene regulatory network (GRN) as a dynamic paramter systems to capture dynamic interaction of genes (parameters) related to neuronal activities of the SNN.

- Functions of neurons and neural networks are influenced by internal networks of interacting genes and proteins forming an abstract GRN model.

- The GRN and the SNN function at different time scales.

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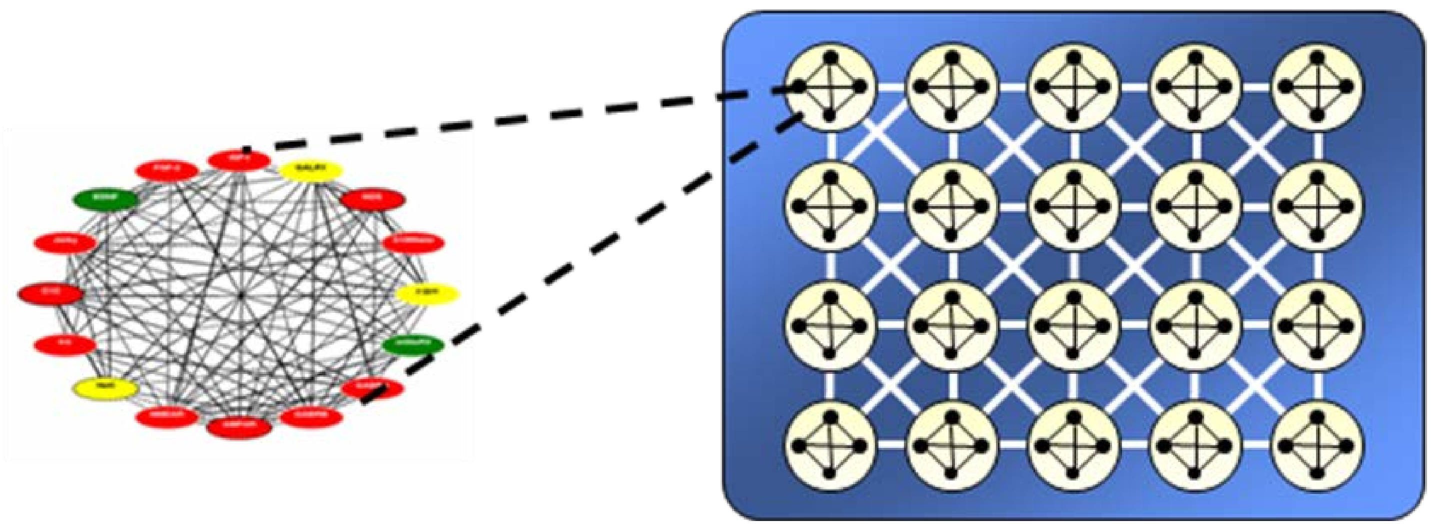
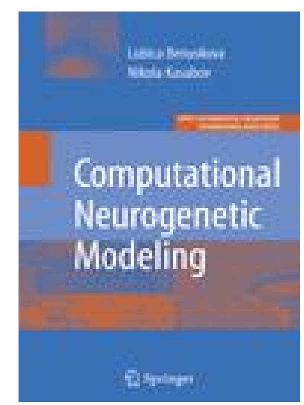
- Benuskova and Kasabov (2007); Meng and Jin (2011)





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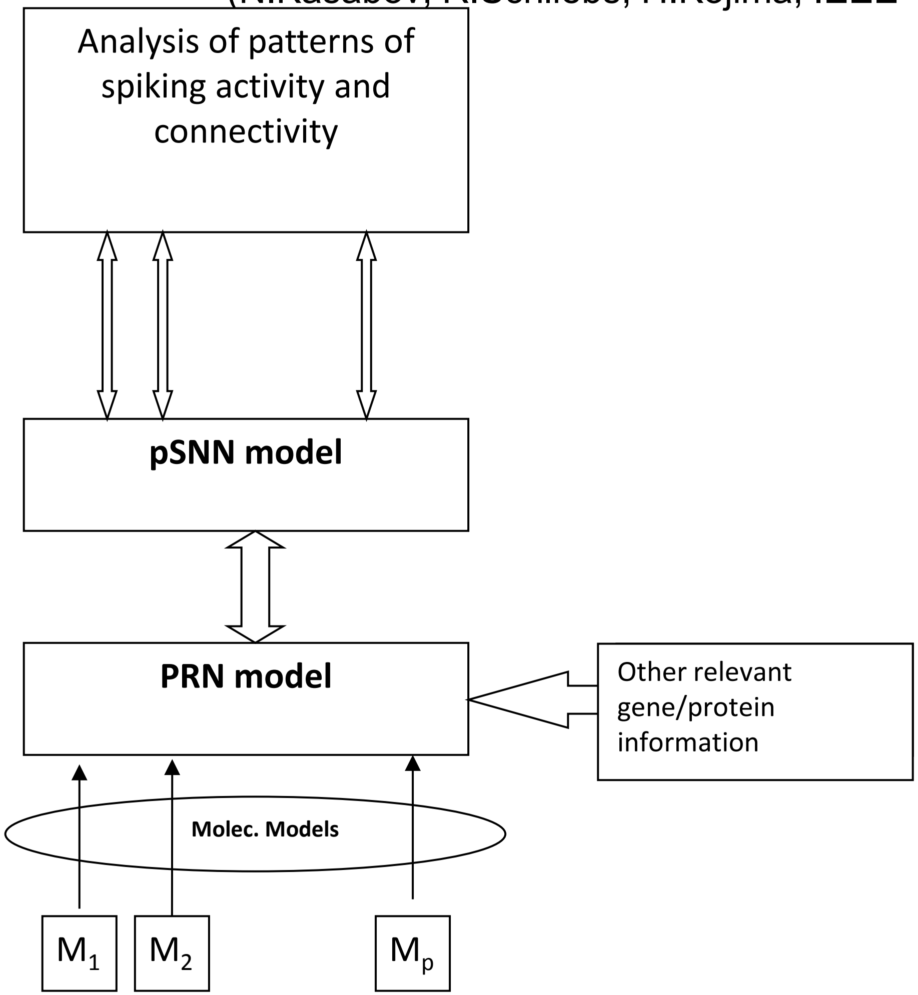
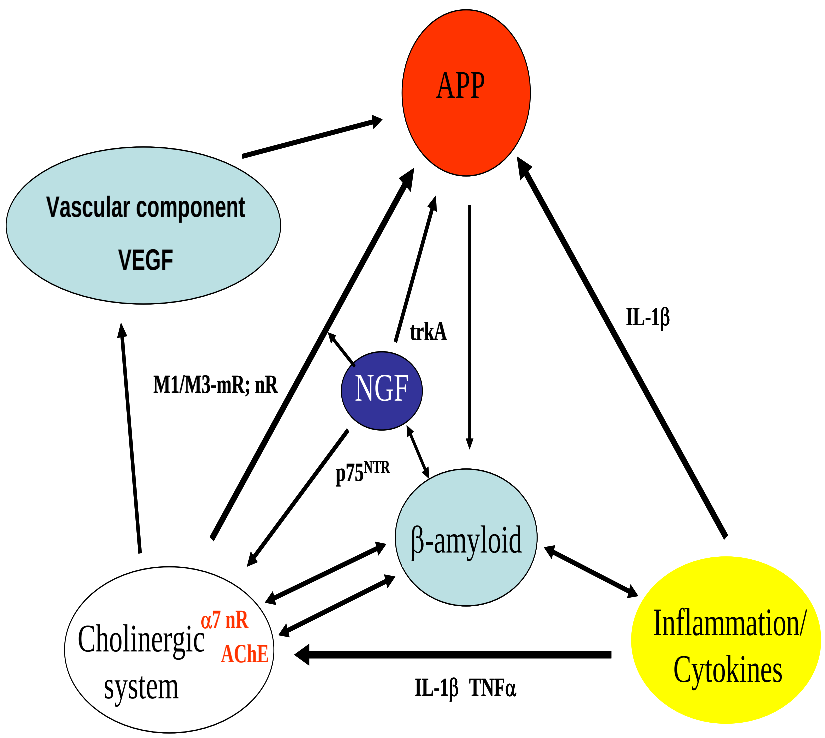
Neurogenetic modelling for cognitive and emotional robots and AD

(N.Kasabov, R.Schliebs, H.Kojima, IEEE TAMD, v.3, No.4, December 2011)





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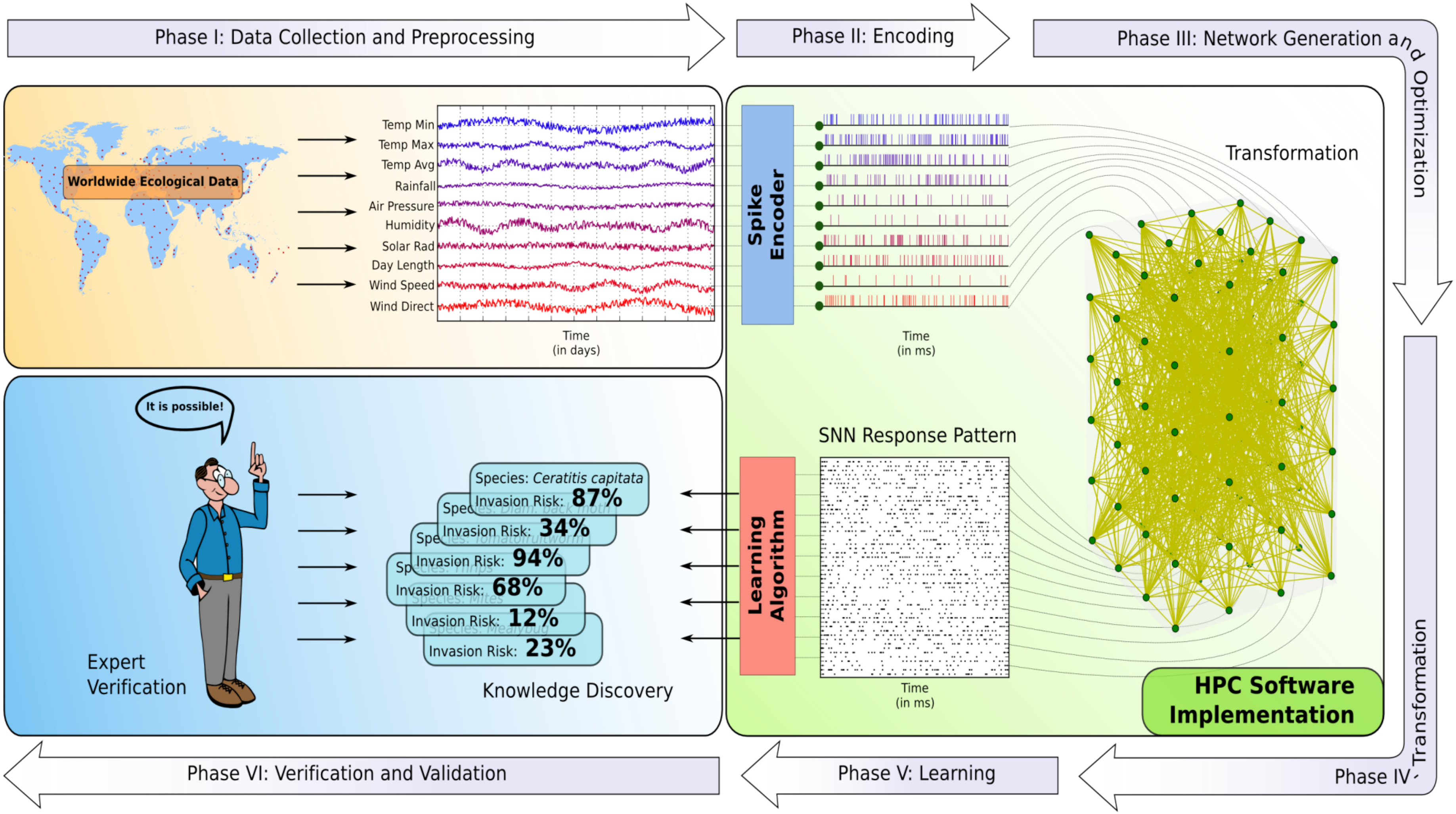
KEDRI

Applications for adaptive, autonomous robots

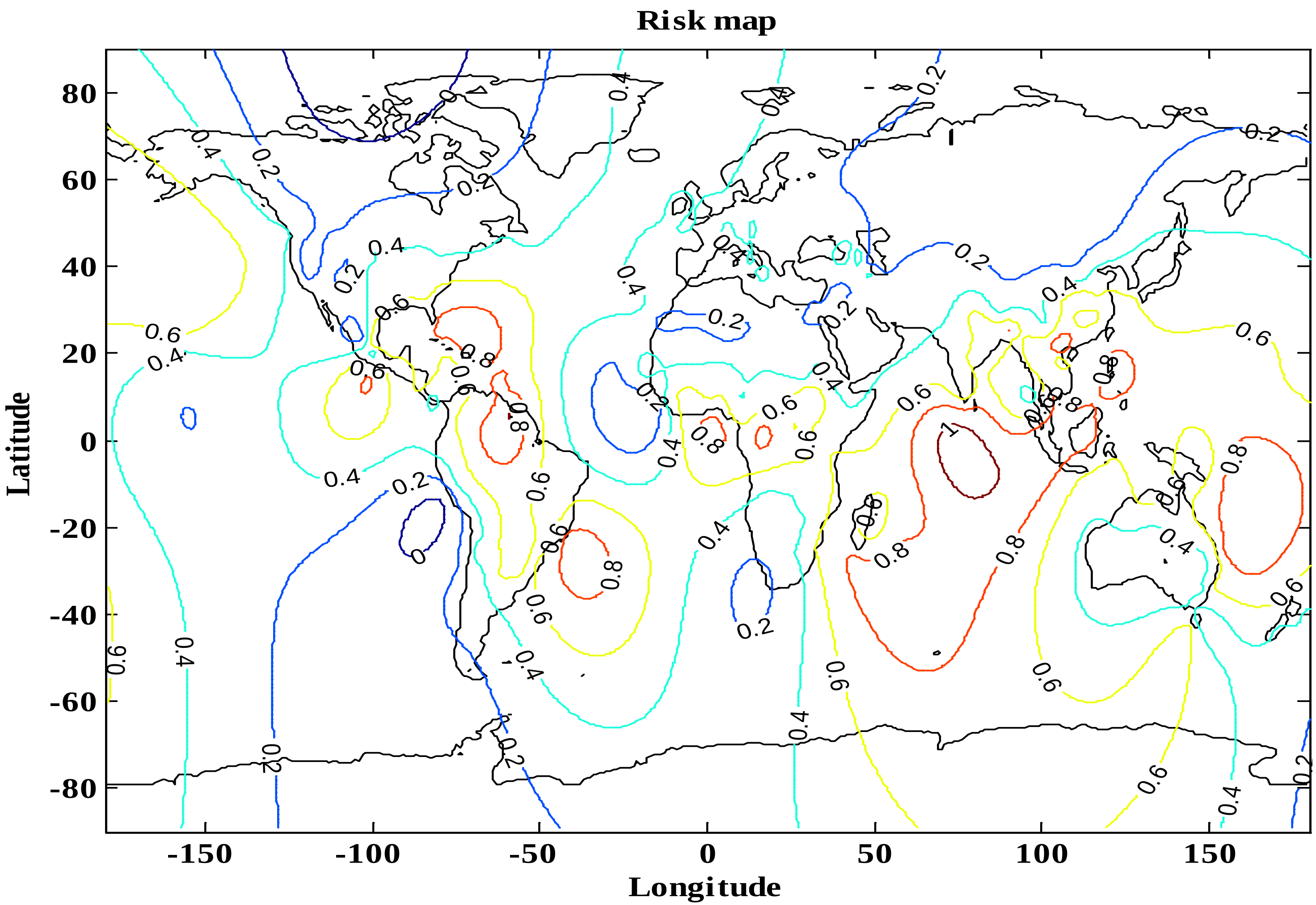
(e.g. work by P.Kormushev –IIT, Genoa; R.Duro – U. la Coruna, P.Angelov – U.Lancaster; KIT Japan; U.Ulster, NASA,)

Estimating the risk of establishment of invasive species on a certain *location* at a certain *time*

(S.Schliebs, Defoin-Platel, N.Kasabov, S.Worner et al, Neural Networks, No.22, 2009)



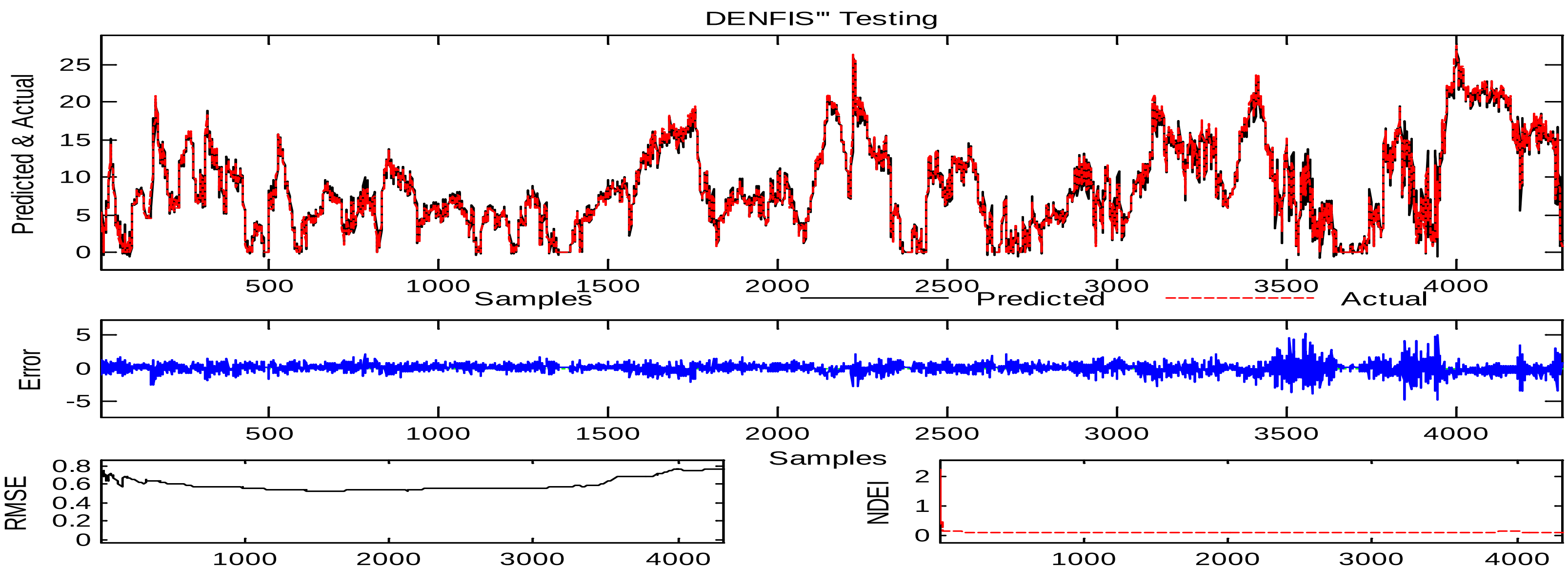
Example: Through modelling a world map was created for the estimation of the probability of *p.citri* insect establishment



Wind energy prediction

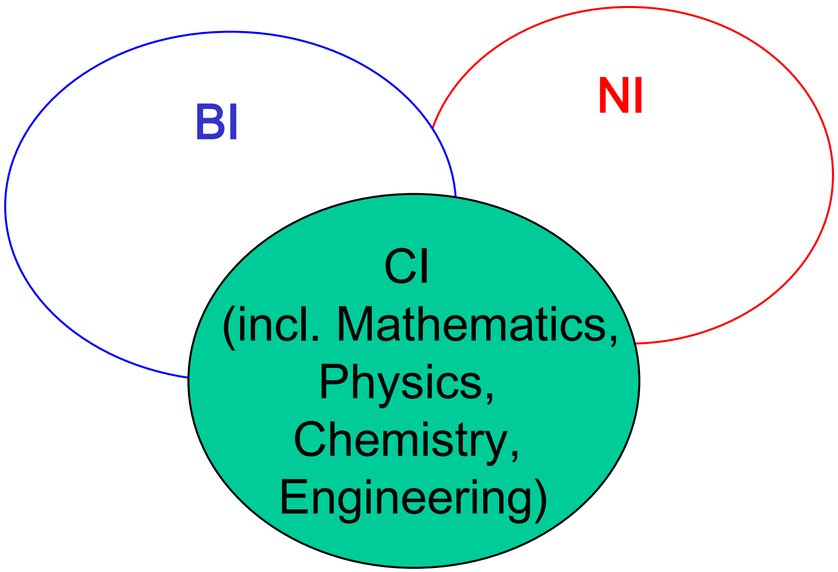
New Zealand

Xinjiang, China (中国新疆)



5. Future Directions

- N*euromorphic system design* for specialised applications such as: Engineering; BCI; Robotics; Neuroprostetics; Environment protection.
- Implementation of EvoSpike models on a SNN supercomputer (e.g. SpiNNacker, U.Manchester) for a large scale spatio-temporal data *mapping, learning and mining.*
- Further interdisciplinary research in the three areas of CI, BI and NI
- The Springer Handbook of Bio-Neuroinformatics, 2013 (N.Kasabov, ed)
- The Springer Series of Bio-Neuroinformatics (N.Kasabov, ed)
- Springer journal *Evolving Systems*



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