Falls Risk Assessment for Hospitalised Older Adults: A combination of motion data and vital signs

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Abstract

Health monitoring systems have rapidly evolved during the past two decades and have the potential to change the way healthcare is currently delivered. Currently hospital falls are a major healthcare concern worldwide because of the ageing population. Current observational data and vital signs give the critical information related to the patient's physiology, and motion data provide an additional tool in falls risk assessment. These data combined with the patient's medical history potentially may give the interpretation model high information accessibility to predict falls risk.

This study aims to develop a robust falls risk assessment system, in order to avoid falls and its related long-term disabilities in hospitals especially among older adults. The proposed system employs real-time vital signs, motion data, falls history and other clinical information. The falls risk assessment model has been tested and evaluated with 30 patients. The results of the proposed system have been compared with and evaluated against the hospital's falls scoring scale.

Keywords: Falls assessment system, automated falls scoring, falls in older adults, older adults falls , Hospitalised falls prevention system and smart falls assessment system.

1 Introduction

Falls and falls-related injuries in older adults are common worldwide and ageing populations will further contribute to an increasing number. Therefore false-related injuries represent one of the most common causes of long-lasting pain, functional impairment, disability and death in the older adult populations [1].

In this context, the operational definition of a fall is critical in order to predict a fall in an older adult [1, 2]. Therefore, the operational definition of a fall with explicit inclusion and exclusion criteria is highly important, and this can create an ultimate boundary between direct and indirect factors. The rate of hospital admission due to falls for people aged 60 and older in Australia, Canada and the United Kingdom ranges from 1.6 to 3.0 per 10000 population per annum [3]. Fall injury rates resulting in emergency department visits of the same age group in Western Australia and in the United Kingdom are higher: 5.5-8.9 per 10,000 population per annum. There are areas in hospital practice that would benefit from interventions to reduce the number of falls and consequent injury [3].

One of ten falls in older adults results in injuries such as hip fractures, subdural hematomas, serious soft tissue injuries and head injuries [4]. In addition to physical injury, falls can also have psychological and social consequences. Fear of falling and post-fall anxiety syndrome are well-recognised negative consequences of falls. The loss of self-confidence that leads to an inability to ambulate safely can result in self-imposed functional limitations [5, 6].

2 Falls Prevention Strategies and Common Risk Factors

Several studies have shown that the risk of falling increases considerably as the number of risk factors increases. Stevens [4] categorised falls risks factors as personal or environmental. Personal factors include characteristics of the individual (such as age, functional abilities and chronic conditions) while environmental risk factors usually refer to fall hazards in and around the home or facility (such as tripping hazards, lack of stair railings or grab bars, unstable furniture and poor lighting). The risk of falling increases with the number of risk factors present and the prevalence of many risk factors increases with age [4].

Falls risk can be reduced by modifying risk factors such as lower-body weakness, problems with gait and balance, use of psychoactive medications and visual impairment. Identifying and treating symptoms of certain chronic diseases such as Parkinson's Disease, delirium, stroke and arthritis may also reduce the risk of falling as indicated by Stevens [4] as well as Oliver and Healey [7].

The Rand Report [8], a systematic review of fall interventions, concluded that falls prevention programs as a group reduced the risk of falling by 11% and the monthly rate of falling by 23%. Interventions that focused on high-risk individuals (e.g., those who had fallen and were at increased risk of falling again) were more likely to be effective than were those that targeted an unselected group of seniors. Based on a meta-analysis of randomised controlled trials, the Rand Report [8] concluded that the most effective intervention strategies used clinical assessment combined with individualised fall risk reduction and patient follow-up. Such an assessment includes testing gait, balance and neurological function, reviewing all medications, developing a tailored medical management approach and making appropriate referrals. When analysed as a group, interventions that used clinical assessment and risk reduction lowered the risk of falling by 18% and reduced the average number of falls by 43% [8].

Prevention of falls and injuries is not easy, however, because falls are complex events caused by a combination of intrinsic impairments and disabilities (i.e. increased liability to fall) with or without accompanying environmental hazards (i.e. increased opportunity to fall) [9]. A fall is classified as a 'complex event' involving more than 'hundreds' of contributing factors. There is some success in falls and/or injury prevention reported in the literature when the some (usually more than one) or all of the following components are included: strength, balance and gait training, improving transferring and ambulation, footwear improvements, investigation and management of untreated medical problems, medication review and adjustment (especially psychotropic drugs), vision tests, hip protectors, patient and staff education about fall prevention, fall risk alert cards, post-fall assessments, and environmental and home risk assessment and management [1, 7, 9].

Multi-disciplinary risk assessment and management strategies are the most effective preventative tools. In most inpatient settings, a member of the nursing staff is generally the first provider to assess the patient for falls risk [7, 10].

There is no single assessment tool for all facilities or patients; however, comprehensive standardised tests and measures with reliability and validity, especially predictive validity, are recommended for use in every setting [5]. In other words, to accurately assign a risk value based on the outcome of a standardised risk screen or assessment, the implement should be employed in populations and settings equivalent to those in which it has been investigated. In the acute care setting, popular tools include the Morse Fall Scale (MFS) [11], the STRATIFY risk assessment tool [12], and the Hendrich Falls Risk Model II (HFRM-II) [13].

The Morse Fall Scale (MFS) [11] scores six areas in the ranges of no risk, low risk, and high risk. The areas include:

- History of falling; immediate or within 3 months
- Secondary diagnosis
- Ambulatory aid
  - Bed rest/nurse assistance
  - Crutches/cane/walker
  - IV/Heparin Lock
- Gait/transferring
  - Normal/bed rest/immobile
  - Weak
  - Impaired
- Mental Status
  - Orientated to own ability
  - Forgets limitations

3 Overview of the Proposed Falls Assessment Model

From the literature [Ref], it is evident that the patient's stationary (fixed) information such as: falls history, age, gender and types of allergies, combined with real-time and continuously changing information such as vital signs and motion data provides higher accuracy in falls risk assessment. Figure 1 shows the overview of the falls assessment model and its key components derived from the literature. Motion data is incorporated into the falls assessment model by using a tri-axial accelerometer which gives walking and activity of daily living (ADL) data. Moreover, real time vital signs are also integrated from the medical devices as well as from the outcome of the physical sign interpretation model. Falls history and types of medication features are fed to the parameter weighted module for the confidence scoring and falls risk assessment (high, medium or low).

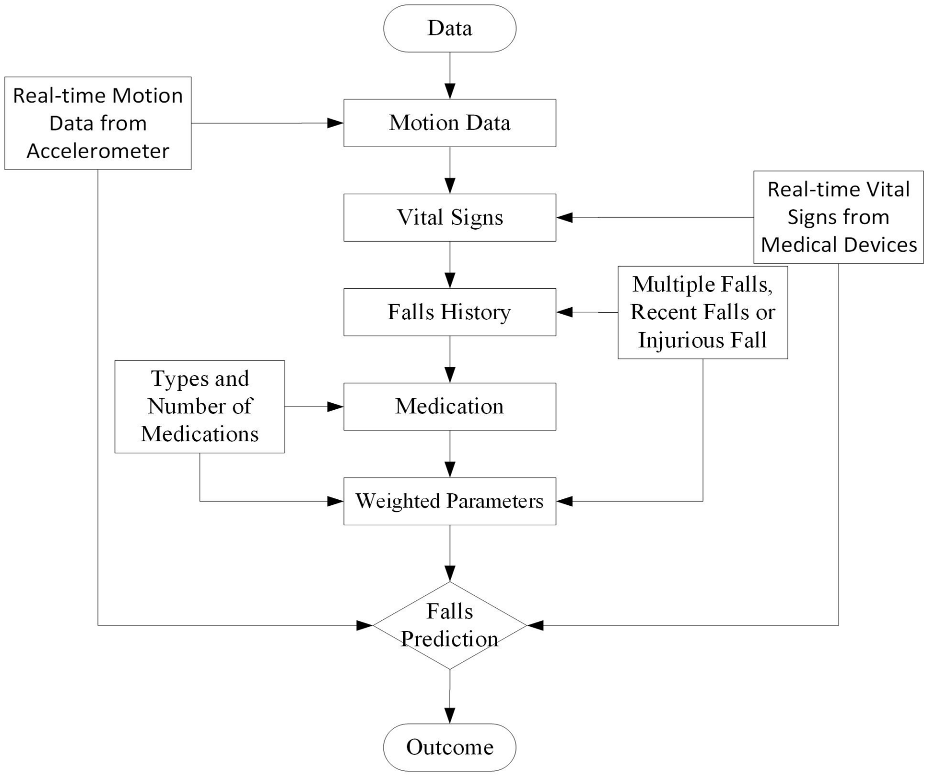

Figure 1 Overview of falls risk assessment model.

3.1 Motion Data Analysis

The device used to collect motion data is the 8XM-3 mini, tri-axial 14-bit ±8g accelerometer from Gulf Coast Data Concepts [14]. This device is attached to the patient's arm for 24 hours and data is stored in the device with a real-time-stamp. The device is compact with the sampling rate of 6 to 200 Hz and can work up to four days continuously. The captured data is stored in the internal 2GB flash memory. To best extract the motion features from the tri-axial accelerometer, a number of methods have been proposed in the literature [15] and their effectiveness varies in terms of successful assessment, but there are numerous algorithms which proved successful in detecting a fall using a similar accelerometer. However, the area of focus is to predict falls in order to prevent them rather than detect the falls 'after the damage (fall) has been done'.

Initially normal motion data patterns from older adults (who did not have any fall history or walking issues) were collected including walking, sitting, stumbling, falling (right, left, backward and forward) with daily life activity (ADL). Total of 20 hours of normal walking data pattern were collected at 100 Hz. This database serves as the core framework for the proposed model. A unique two-way classification model was adopted based on the collected information. Firstly, threshold based detection is adopted, where threshold limits are set by analysing the collected data patterns comprising: gait speed, step length, sway and asymmetry of gait; data points exceeding those set threshold limits for each activity were considered ‘not normal’ motion data patterns and can be further elaborated into low, medium or high risk depending upon the mean or SD values of exceeded limits.

Secondly, motion data from the accelerometer was compared against the already collected database in a moving window analysis (5 second, 10 second or 15 second window) in each particular activity (sitting, walking, standing, etc.). The falls assessment model uses both methods; in the case of incomplete information the earlier method (stand-alone) works well and if the information is complete (at the end of each time window), then both methods will contribute towards the falls assessment.

3.1.1 Detection of Unstable Pattern

Accurate identification of normal and abnormal or unstable patterns are critical in this system an over-estimation can lead to a ‘normal’ patient being exposed to high falls risk management (with potential adverse consequences). Under-estimation can lead to grave consequences, where a high falls risk patient can be classed as a low or no falls risk. Detection of Sitting vs. Stumbling vs. Fall Patterns

Classifying each event accurately is critical for this model to predict the deterioration in the patient’s motion data when compared to the normal data trajectories. The model accurately classifies various events with unique activity-based classifiers for each activity/event. Figure 2 shows the accurate classification of sitting on a chair, stumbling to the left and an intended forward fall in a ‘normal’ patient data pattern. Each classified event is validated and confirmed with the manually maintained observational notes throughout the walking activity. Figure 3 shows the detection of stumbling to the left and a fall on the bed (which may indeed be a risk factor for falls but is not within the accepted definition of a fall), it is important to annotate that the classifier accurately detected the fall on the ground as well as the fall on the bed.

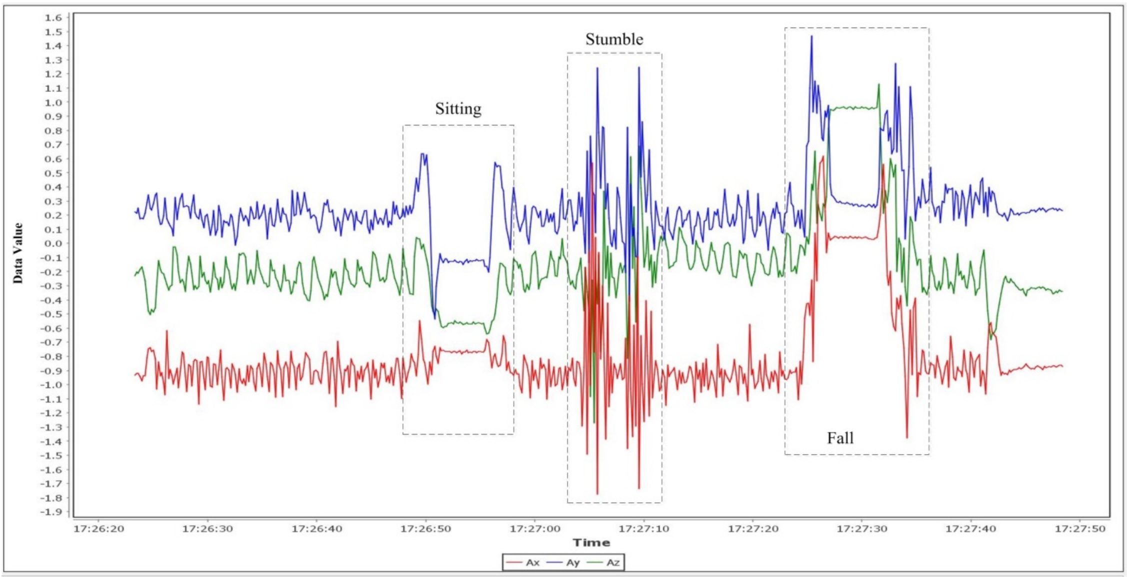

Figure 2 Identification and classification of sitting, stumbling and falls patterns in a healthy person.

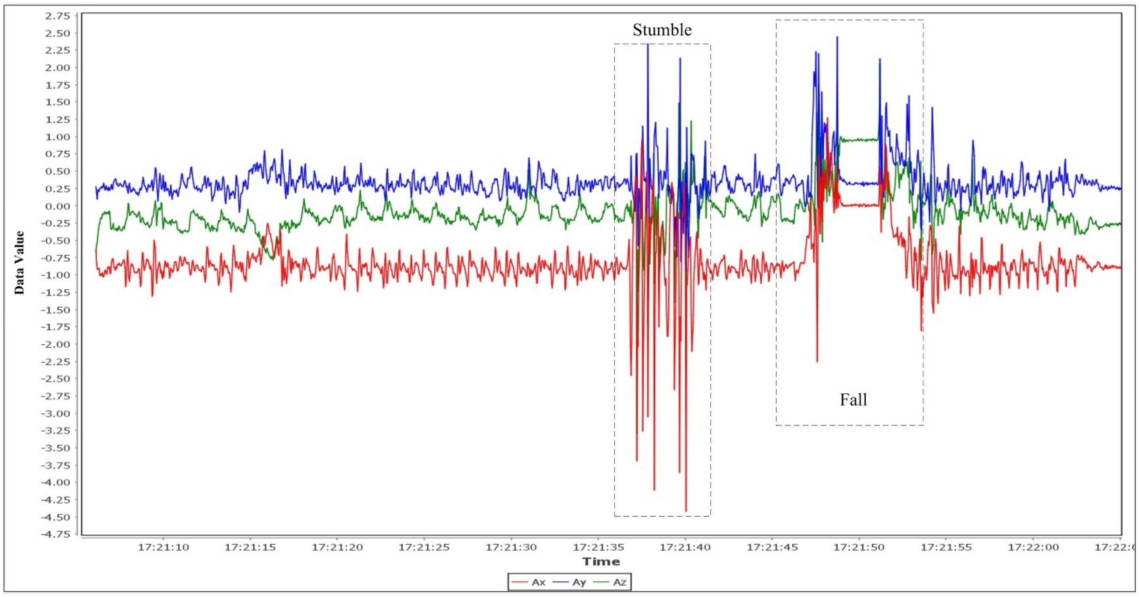

Figure 3 Identification and classification of stumble and fall in a hospitalised patient.

3.2 Real-time Vital Signs

Integration of vital signs into the falls risk assessment system gives an enormous advantage to the proposed model in identification, detection and classification of falls risk. Integration of vital signs has been poorly addressed in the literature [7, 16]. However, there is a good report for concrete association between the vital sign(s) and falls [17]. One of the expert rules/conditions adopted here is the case of postural hypotension where:

'A fall of more than 20 mmHg in systolic blood pressure and/or more than 10 mmHg in diastolic blood pressure when standing (compared to the sitting blood pressure) indicates risk of fall' [17].

Figure 4 shows the model design overview. A direct link between the vital signs and the falls assessment model was implemented as well as a link between identified physical signs and overall weighted parameters which also contribute to the falls risk assessment. Direct and indirect links between the input and the output have been maintained throughout the design and development due to the fact that the clinical situation, particularly of hospitalised patients, is often variable (unstable) over days or even hours. The integration of the proposed model with direct/indirect incorporation of real-time vital signs towards the falls risk assessment has given the proposed model a unique tool in falls risk assessment.

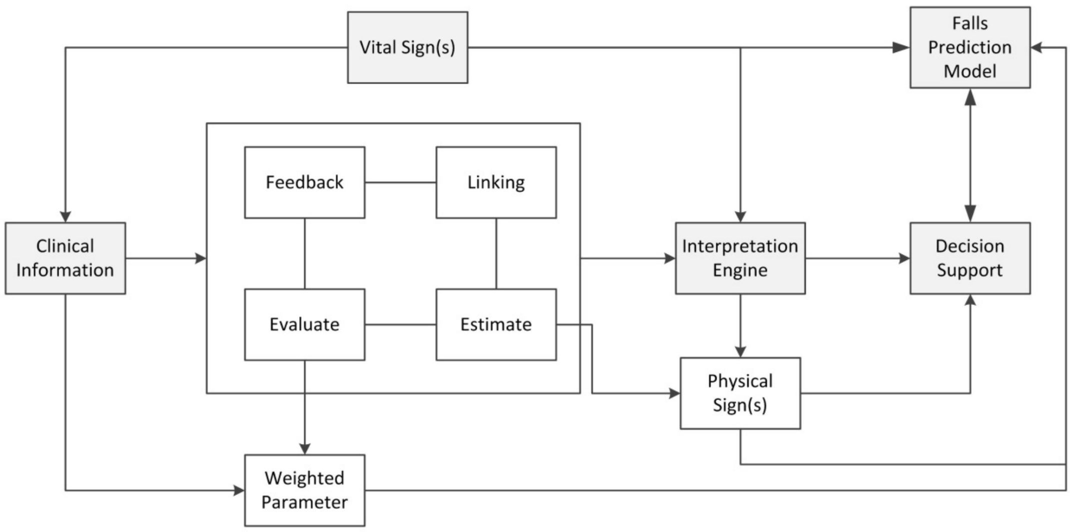

Figure 4 Block diagram of vital signs linkage with falls assessment model.

3.3 History of Falls

Information about the previous falls is advantageous for the future falls risk assessment [1, 7, 16, 18]. In the proposed model, three main phases are considered for falls risk assessment; past history, current status and any ongoing falls-related illness as shown in the Figure 5.

Firstly, the 'recent falls' tab checks falls less than three months or six months before hospital admission, then the model also makes notes of the walking aid (if any) the patient is currently using. Secondly, the number of previous falls is considered (excluding the ‘recent falls’) in order to help categorise the risk of future falls. Finally, the injurious falls tab identifies the type (if any) of injury or injuries due to the previous fall(s). This can indicate any short-, medium- or long-term disability in relation to the recent or the previous falls.

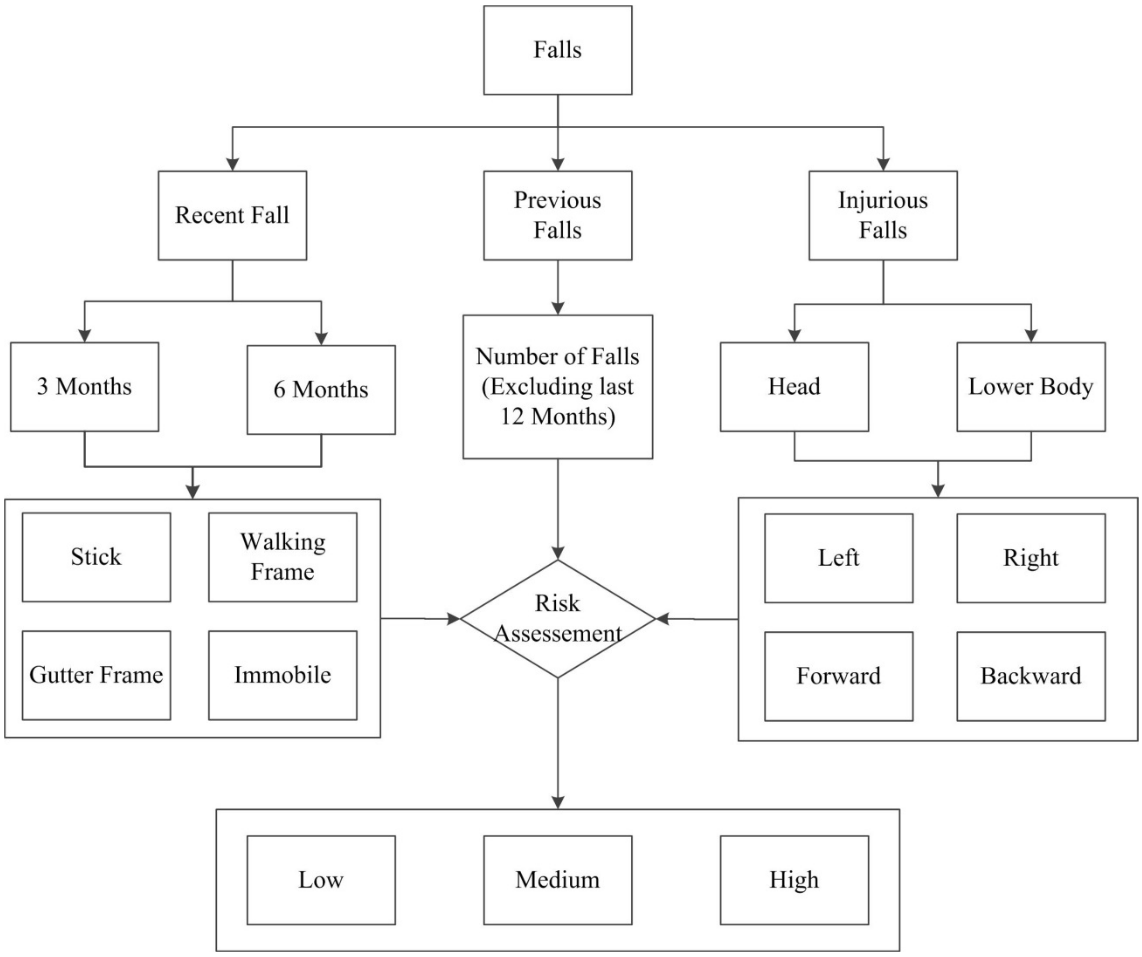

Figure 5 Flow diagram of patient's fall history.

3.4 Medications

Another critical factor that has been widely adopted in the majority of falls risk assessment tools is the relationship between falls risk and the use of different types of medications. It is reported in the literature that there is an association between falls and medication, which indicates that falls risk increases with the increase in the number and types of medication.

Figure 6 shows the basic classification adopted by the proposed model in falls risk assessment. The inclusion of all drugs is beyond the scope of this research and requires the inclusion of a complete list of drugs legally allowed in New Zealand hospitals by the Ministry of Health, and running of that list into the structured query language (SQL) database (server), which is a big task by itself. Instead the proposed model classifies the risk factors as low for zero to four different types of medications and medium risk for four to six types and six or more different types of medication are categorised as high risk [4]. The number of different types and number of medications is entered by the clinician into the system.

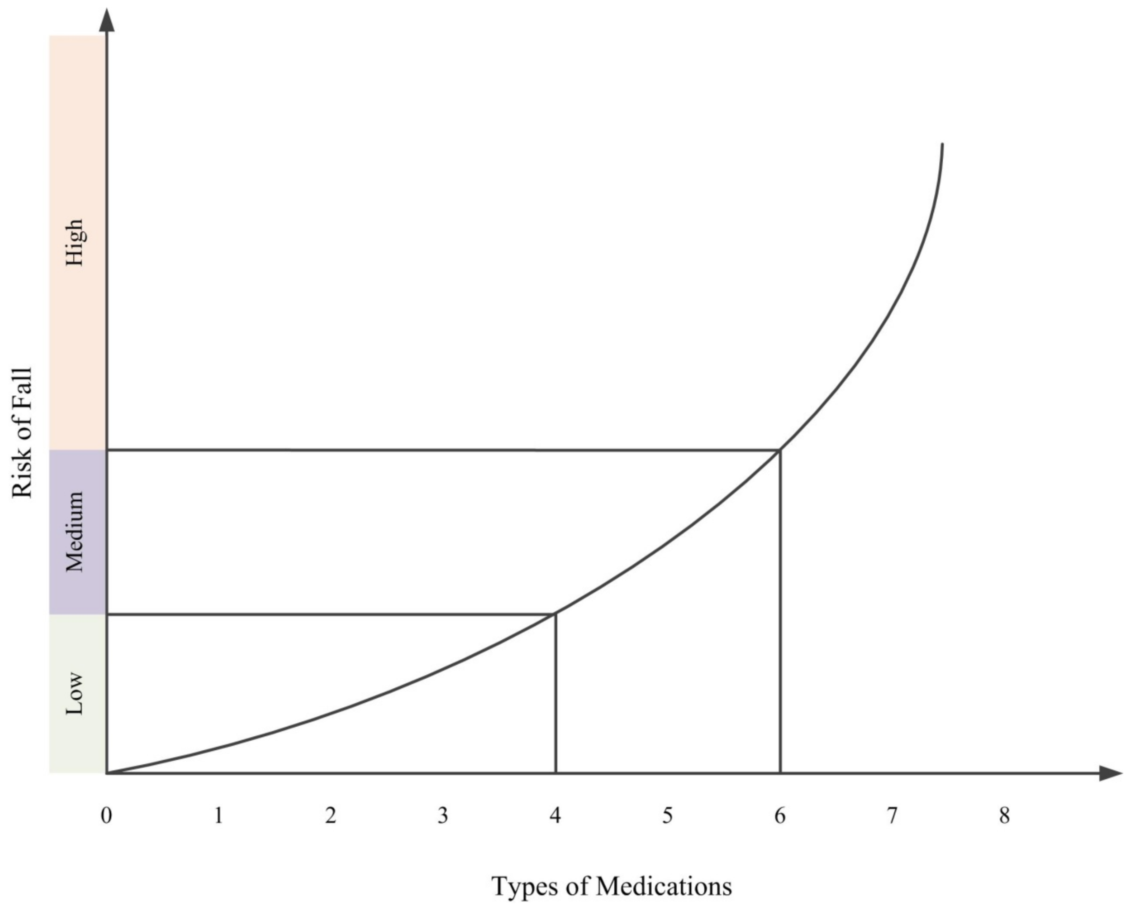

Figure 6 Graphical illustration showing increase of falls risk with increase in number of different types of medications [4].

3.5 Weighted Parameters

Outcome information is gathered from all of the modules described above to calculate the confidence score. Specifically, for falls risk assessment scoring, the calculation carried out by the weighted parameters module is by assigning direct and indirect links. For instance, high weightage is given to ‘Low BP’ because of the direct relation to falls, whereas less weight is given to T or SpO2 because of their indirect (not absent e.g. pneumonia) relationship to falls. All the scores from other modules are summed up and confidence ratings are given to each factor in predicting low, medium or high falls risk. From all gathered information, for each module the system sets points that will be forwarded to the weighting parameter module for possible risk assessment scoring (Scoring is further discussed in results section of this paper).

3.6 Falls Classification Mechanism

When falling, the person frequently hits the ground or an obstacle. The 'sudden rise' results in an intense inversion of the polarity of the acceleration vector in the direction of the trajectory, which can be detected with an accelerometer or wave peak detector, with a previously determined fixed threshold limit/range. Even if most of the falls occur in the "frontal" plane (forwards or backwards), the direction of the fall trajectory is obviously variable from one fall to another. Also the location of the sensor on the body related to the point of impact modifies the "signature" of the signal recorded at the time of the falls. Lack of movement is also used to detect the fall as, after a "serious" fall, where the person may be seriously injured, they frequently remain immobilized in a posture and/or a place. A movement classifier is used to detect that 'silent phase'.

It is observed that during a fall there is a temporary period of "free fall", during which the vertical speed increases linearly with time due to gravitational acceleration. The vertical speed of controlled movements of the person (to rise, bend down, sit down) is measured to discriminate these speeds from those occurring during a fall, which exceed an appropriate fixed threshold as well as considerable changes being observed from the normal data pattern. The range gap is very narrow and the difficulty lies in the choice of this threshold, if it is too low the device also detects negative events ("false positive"); when the threshold is too high it does not detect positive events ("false negative"). This threshold is also dependent on the subject-to-subject variability.

To overcome this critical issue, a learning period of either "supervised" or "unsupervised" learning is adopted using the database which has various activities and patterns for model learning. During data collection of normal walking patterns, the statistical information such as normal speed of sitting on a chair, lying on a bed and standing are recorded. Then in real-time data analysis, each recorded measurement is checked to carry out a statistical analysis on measured speeds of each patient individually.

3.7 Risk assessment

Falls and fall-related injuries represent an enormous burden to individuals, society and health care providers. Because the population is ageing, this problem will increase unless vigorous preventive action is taken. There is a need to refine, promote and implement effective interventions. In addition, more information is needed in order to tailor interventions for populations with differing characteristics and risk factors.

The pattern recognition classifier accurately detects and classifies the difference between a fall on the ground and a fall on the bed, a stumble to the right and left, sitting on the chair and a fall onto a chair. A falls detection model using motion data alone as well as a combination of motion data and vital signs was also explored [ref: : Challenges, issues and trends in fall detection systems. Igual R., Medrano C., Plaza I., BioMedical Engineering OnLine 2013, 12:66 doi:10.1186/1475-925X-12-66]. More focus has been given to the falls risk assessment and classification model when compared with the detection of falls. Figure 7 shows the overall architectural data model of the proposed system representing key modules and their linkage.

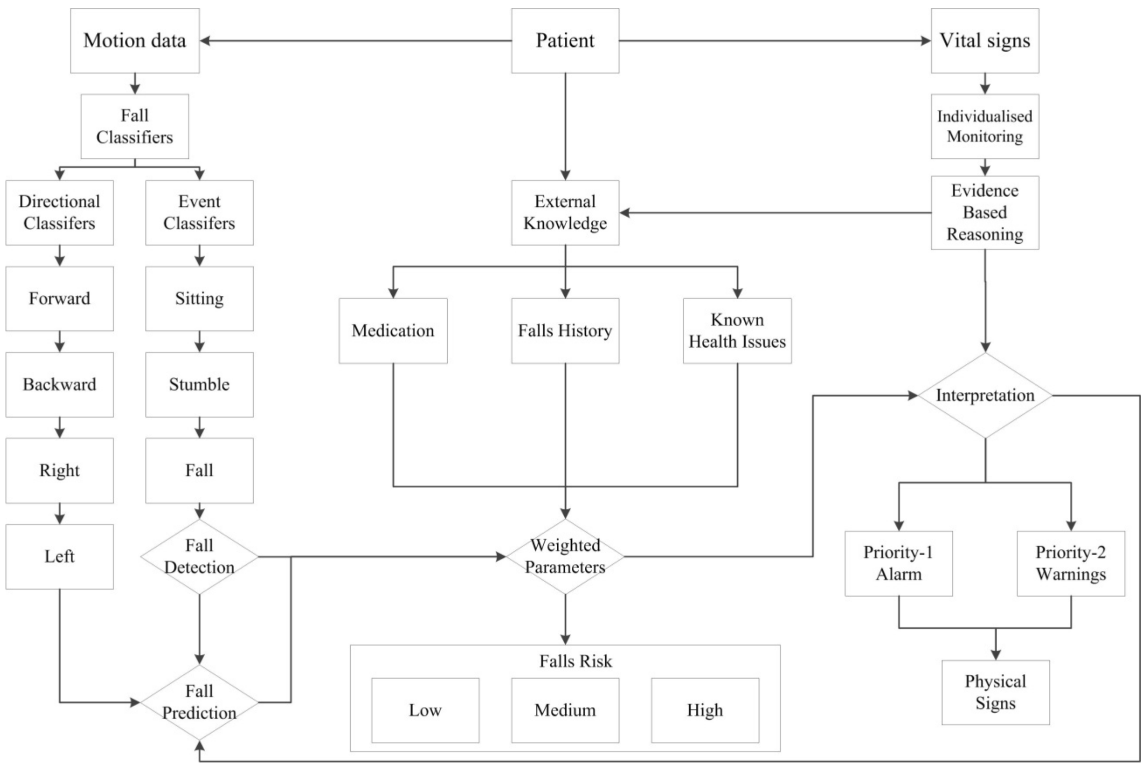

Figure 7 Architectural data model of the proposed system representing key modules and their linkage.

The proposed model has been tested with healthy older people, hospitalised older patients, intentional falls and other daily life activities. Extensive data analysis and pre-processing is carried out on the tri-axial accelerometer data so that the input data carries maximum features for the classifiers to detect.

4 Results and Validation

4.1 Accuracy Evaluation of Falls Risk Assessment Classifiers

In order to evaluate the falls risk assessment classifiers of the proposed model, four healthy male individuals (aged 62Y, 69Y, 72Y and 75Y respectively) performed intentional falls and normal activities of daily life (ADLs). For testing and evaluating the system individuals with impaired vision, imbalance, walking with any support or cognitive impairment were excluded. Activities performed included forward, backward, right-side and left-side falls as suggested by Noury et al. [19]. A total of 80 intentional falls and 40 ADLs were simulated as shown in Table 2.

Table 1 Accuracy results of the proposed system when detecting backward, forward, right side and left side falls.

Category	*TP*	*TN*	*FP*	*FN*	*Accuracy %*
Forward Fall	20	20	0	0	100
Backward Fall	18	18	0	4	90
Left-side Fall	17	17	0	6	85
Right-side Fall	19	19	0	2	95
Total	74	74	0	12	

4.2 Testing of Falls Risk Assessment Model

As mentioned earlier, a similar data processing process was followed here with ten patients' data used for initial testing and training of the falls assessment model. The remaining 20 patients' data was used for real-time testing. Figure 8 shows the falls risk assessment results by the proposed system and categorises them into high, medium and low falls risks. The numbers in the bracket are the falls risk results obtained from the Morse falls scale (MFS), performed by (blinded) medical staff on the same 20 patients.

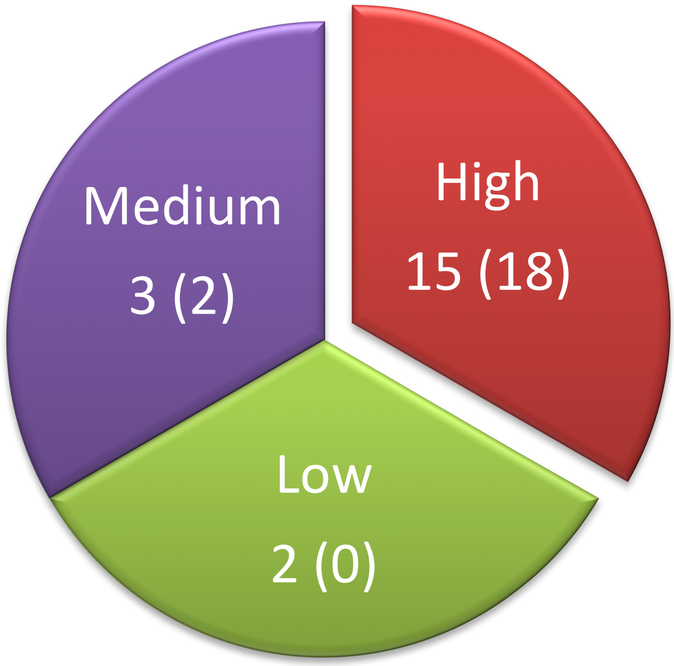

Figure 8 Total number of falls risk assessment by the proposed system with high, medium and low classification. Numbers in the bracket are blinded Morse Falls Risk results for the same patients.

Table 2 shows the both proposed system and MFS agreed and were positive 15 times for high risk and twice for medium falls risk (TP = 15) while the system was positive and MFS showed negative assessment three times (one for medium risk and two for low risk) (FP = 3). There were two incidents recorded where the system was negative and MFS was positive (FN = 2), and there were no incidents recorded where the system and MFS were both negative (TN = 0).

Table 2 TP, TN, FP and FN values extracted from 20 patients' data for qualitative analysis.

System/MFS	*MFS (+ve)*	*MFS* (-ve)*	*Total*
System (+ve)	15 (TP)	3 (FP)	18
System (-ve)	2 (FN)	0 (TN)	2
Total	17	3	20

*MFS is Morse Falls Scale

From the above obtained values the proposed system achieved an accuracy of 75%, sensitivity of 88% and predictability of 83%, against the Morse Scale. The best available option for the evaluation of the proposed system results is comparing them with MFS risk assessment scores. The MFS categorised the falls risk scoring as: everyone (0-24), medium (25-44) and high (45+). It should be mentioned that from the whole 30 patient data, the MFS indicated only two patients as medium risk and the remaining patients (28) as high risk, giving the high risk indication of 93%. As mentioned earlier, further prospective validation of the system (i.e. its ability [vs the MFS] to predict actual falls) was not possible for the proposed system in real time as this would have required requires a larger study over a longer time period (the duration of inpatient stay for many more than 30 patients).

MFS is a manual falls scoring scale which uses falls history, secondary diagnosis, aid, IV infusion, gait and mental status to predict the risk of falls, whereas the proposed monitoring system uses real-time vital signs, real-time motion data (walking pattern), falls history and types of medication and integrates the gathered information into the weighted parameter module for the falls risk assessment. The above-mentioned results can be considered as the comparison between two (technically) different methods/models and it is not possible (in the absence of the prospective study discussed above) to conclude which one is more accurate. However the system described here has reasonable agreement with the MFS, a previously validated and widely adopted scoring tool in hospitals. The proposed model has the advantage of using real-time component and it is a real-time computerised monitoring system. It may be that the new system has either greater, lesser or similar predictive ability to the Morse Scale. Elucidation of this will be the subject of further research

5 Discussion and Conclusion

The proposed falls model was developed to establish a robust method in which effective falls risk assessment can be used to minimise the personal and financial cost of associated injuries in hospitalised older adults. It also aimed to minimise false alarms which are a nuisance for patients and caregivers and can compromise effectiveness of care [20]. Users' needs and clinicians' preferences were taken into account and non-invasive, wireless and body-worn sensors were employed in the design of the proposed system [21].

In many fall detection research studies, the starting point of algorithm design has been to set the threshold(s) to the same level as the slowest fall event. The proposed system introduced a novel method by including real-time vital signs and motion data with falls history and types of medication to reduce the false alarms, which can be a serious problem for nurses looking after several patients. This can be done by categorising falls by means of directional/postures sub-categories combined with incoming real-time vital signs. Reducing false alarms makes the fall detection system comfortable to use for the clinicians. Another addition to the existing falls prevention model could be the inclusion of more structured input information from clinicians as well as patients, such as body mass index, height, weight, urinary frequency, confusion, footwear and clothing and other known health issues, specially arthritis, osteoporosis, diabetes and high blood pressure [22].

There is now strong evidence that a clinically important proportion of falls experienced by older adults are preventable. However, further research needs to be done to determine the actual predictive value of the new system in a prospective trial, what type of falls can be prevented and if/how older adults can benefit from interventions by computerised systems. Those who could benefit may be identified by individual assessment and by studying the characteristics of falls. Current monitoring devices are not designed to replace healthcare professionals, but rather to support them in making decisions in complex situations through more rapid processing of patient information and thus speedier delivery of treatment. A more effective means of delivering proven interventions and treatments to reduce the risk of falls is required.

Conflict of interest statement

Authors declare no conflict of interest.

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