Original Article

A system for improving fall detection performance using critical phase fall signal and a neural network

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Abstract

We present a system for improving fall detection performance using a short time min-max feature based on the specific signatures of critical phase fall signal and a neural network as a classifier. Two subject groups were tested: Group A involving falls and activities by young subjects; Group B testing falls by young and activities by elderly subjects. The performance was evaluated by comparing the short time min-max with a maximum peak feature using a feed-forward backpropagation network with two-fold cross validation. The results, obtained from 672 sequences, show that the proposed method offers a better performance for both subject groups. Group B's performance is higher than Group A's. The best performances are 98.2% sensitivity and 99.3% specificity for Group A, and 99.4% sensitivity and 100% specificity for Group B. The proposed system uses one sensor for a body's position, without a fixed threshold for 100% sensitivity or specificity and without additional processing of posture after a fall.

Keywords: fall detection, critical phase, short time min-max feature, accelerometer, neural network

1. Introduction

The number of elderly (i.e. people aged over 60 years) is growing faster than any other age group, and is estimated to reach almost two billion by 2050 (United Nations, 2009). Falls in the elderly, and consequential injures, are major public health problems. The World Health Organization reported that major causes for fall-related hospital admissions are hip fractures, traumatic brain injuries, and upper limb injuries, and their healthcare costs are increasing significantly (World Health Organization, 2008), ranging from US$ 6,646 in Ireland to US$ 17,483 in the USA is the average cost of hospitalization for fall-related injuries for people aged 65 years and older (Carey *et al.*, 2005; Roudsari *et al.*, 2005). The

severity of the injury and the cost could be reduced if the elderly could get help immediately after a fall.

The two most popular techniques for fall detection research utilize image processing and sensors (Noury *et al.*, 2008). Sensor methods perform very well (Lin *et al.*, 2007; Kangas *et al.*, 2008; Kangas *et al.*, 2009; Chao *et al.*, 2009; Bourke *et al.*, 2007; Bourke *et al.*, 2008; Bourke *et al.*, 2010; Jantaraprim *et al.*, 2009; Jantaraprim *et al.*, 2010; Jantaraprim *et al.*, 2012) without limitation of lighting and framing, while the limitation appears in image processing method (Huang *et al.*, 2007; Nyan *et al.*, 2008; Lee *et al.*, 2007; Lai *et al.*, 2008).

For ethical reasons and due to safety and health concerns, all fall experiments were performed by young subjects falling onto a mattress. Normal activities or Activities of Daily Living (ADL) were performed by young/elderly subjects. A young subject for Lin's study (Lin *et al.*, 2007) with results of 98-100% sensitivities, nine micro mercury switches and an optical sensor attached to ten places around a coat to detect fall after impact. Three middle aged subjects

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for Kangas's study (Kangas *et al.*, 2008), a tri-axial accelerometer attached to the waist or head for fall detection. Two or more phases of a fall event were employed in his study: the beginning of the fall, falling velocity, fall impact, and subsequent posture of the person. Using a simple threshold with three different detection algorithms (impact + posture, start of fall + impact + posture, and start of fall + velocity + impact + posture) and setting a threshold for 100% specificity, his studies reported a sensitivity of 97-98%. Recently, he studied the same algorithms with more subjects, 20 middle-aged subjects performed both intentional falls and ADL, and 21 older people performed only ADL. His study obtained a sensitivity of 97.5% and a specificity of 100% (by setting thresholds) (Kangas *et al.*, 2009). Chao (Chao *et al.*, 2009), whose study involving seven young males performed both fall and ADL, proposed the acceleration cross-product (AC) as a parameter for fall detection, and compared to the acceleration magnitude (AM). The AC leads to a larger area under a receiver operating characteristic curve than the AM. Furthermore, false alarm ratios were reduced for including post-fall posture (PP) recruitment for both AC-based method and AM-based method. Sitting-to-lying motion was reported to produce false alarms in his study. Bourke, whose studies involving ten young subjects performed fall and ten elderly subjects performed ADL, studied fall detection using a biaxial gyroscope (Bourke *et al.*, 2008), a tri-axial accelerometer (Bourke *et al.*, 2007), and an inertial sensor (a tri-axial + a gyroscope) (Bourke *et al.*, 2010). Using a threshold-based algorithm, 100% sensitivity (by setting thresholds) and 100% specificity was reported in his studies. However, our study of the same algorithm (Jantaraprim *et al.*, 2009) used in Bourke's study (Bourke *et al.*, 2007) found that some false positives occur in the case of quick movements. This was confirmed in his recent work with scripted and unscripted activities (Bourke *et al.*, 2010), which utilized thresholds for velocity, impact, and posture to achieve 100% sensitivity (by setting thresholds) and 100% specificity. His study (Bourke *et al.*, 2010) needs signal from both an accelerometer and a gyroscope to find velocity.

The above-mentioned studies involving only elderly ADL (Bourke *et al.*, 2007; Bourke *et al.*, 2008; Bourke *et al.*, 2010) can achieve a better performance than those using young ADL (Lin *et al.*, 2007; Kangas *et al.*, 2008; Kangas *et al.*, 2009; Chao *et al.*, 2009). This was confirmed in our previous studies (Jantaraprim *et al.*, 2009), comparing about different subject groups. Even though most studies give high performance, a posture after fall is needed such as addition of posture after a fall for Kangas's works (Kangas *et al.*, 2008; Kangas *et al.*, 2009), post-fall posture recruitment for Chao's work (Chao *et al.*, 2009), and posture after a fall for Bourke's work (Bourke *et al.*, 2010). These added features require more processing. Some studies showed performance using a fixed threshold of 100% sensitivity or specificity. However, it is better to exhibit performance without a fixed threshold.

During the critical phase of a fall, the body moves suddenly towards the ground, ending with a vertical shock.

During post-fall phase, the body remains inactive, frequently lying on the ground (Noury *et al.*, 2008). The body action during critical and initial post-fall phases produces high negative and positive peak of resultant acceleration of the torso. The short time min-max feature was proposed for our previous study (Jantaraprim *et al.*, 2012) for fall detection for the elderly. The feature used in the study employs specific characteristics of high negative and positive resultant acceleration peaks in short time, which occur during the critical phase fall signal, to detect falls. Even though high negative and positive resultant acceleration peaks are displayed in critical and initial post-fall phase, they occur in the critical before the initial post-fall phase. Thus, these specific characteristics are detected in critical before initial post-fall phase. The short time min-max feature can distinguish falls from ADL, which usually have low negative and/or positive resultant acceleration peaks.

The aim of this study was to show that the system consisting of short time min-max feature observed during a critical phase fall signal of a torso and a neural network can distinguish falls from ADL. In addition, there is no need for processing of the posture after a fall and no need for computing a fixed threshold to achieve 100% sensitivity or specificity. The performance of the proposed system was validated and compared with a maximum peak feature, which is a classical feature involved in previous research using a tri-axial accelerometer (Kangas *et al.*, 2008; Kangas *et al.*; Chao *et al.*, 2009; Bourke *et al.*, 2007; Bourke *et al.*, 2010). Results show that the proposed system can achieve a better performance for both ADL subject groups, Group A: ADL by young subjects and Group B: ADL by elderly subjects. In addition, the improvement from a neural network in this study is better than that from the support vector machine shown in our previous work (Jantaraprim *et al.*, 2012). The rest of this paper is organized as follows. Section 2 describes materials and methods; Section 3 presents results; Section 4 contains discussion. Finally, conclusions are given in Section 5.

2. Materials and Methods

Two subject groups were tested in this study. Group A involved the simulated falls and ADL by young subjects. Group B was the simulated falls by young subjects (the same from Group A) and ADL by elderly subjects. This experiment used data from our previous study (Jantaraprim *et al.*, 2010), and added more subjects.

2.1 Experimental setup

As in our previous study (Jantaraprim *et al.*, 2012), two dual-axis MEMS accelerometers (Analog Devices ADXL321) were constructed as a tri-axial accelerometer, and attached to a person's torso as shown in Figure 1. The x, y, and z axes are anterior-posterior, left-right, and superior-inferior, respectively. Signals from each axis were transmitted by wires connected to each accelerometer, transformed from

analog to digital by NI-USB6008, and recorded for later offline processing. All signals were acquired at 12-bit resolution with a 1-kHz sampling frequency, and processed by a second order low-pass Butterworth digital filter with a cut-off frequency of 20 Hz. The trial protocols were approved by the Research Ethics Committee of the Electrical Engineering Department of Prince of Songkla University. Written informed consent was obtained from all subjects prior to the experiments.

2.2 Fall and ADL experiments

Fall detection performance was evaluated using a predefined set of falls and ADL common to the elderly. For ethical reasons, all fall experiments were performed by young subjects falling onto a mattress. Male and female numbers were the same: 14 young subjects (7 male and 7 female, age 25.14 ± 5.26 years) and 14 elderly subjects (7 male and 7 female, age 68.28 ± 4.37 years). There are four categories of fall: forward fall (FF), backward fall (BF), left side fall (LF), and right side fall (RF), and six categories of ADL: sit-stand (ST), stand-sit (TS), sit-lie (SL), lie-sit (LS), bend down to pick up an object (BD), and walk (WA). Each fall and ADL group was repeated three times for each subject. The data comprised 672 sequences, made up of 168 fall sequences, 252 ADL sequences for the elderly, and 252 ADL sequences for the young subjects.

2.3 Features for fall detection

Features are from our previous study (Jantaraprim *et al.*, 2012): maximum peak and short time min-max features. An example of a backward fall is displayed in Figure 2 to show how to find features. Using a tri-axial accelerometer, the backward fall is displayed in terms of x, y, and z accelerations in Figure 2a and resultant acceleration ($A_{res} = \sqrt{\left(A_x\right)^2 + \left(A_y\right)^2 + \left(A_Z\right)^2}$) is illustrated in Figure 2b.

2.3.1 Maximum peak feature

The maximum peak, $\max(A_{res})$, denotes impact and acts as a baseline for measuring fall detection, because a fall produces high resultant acceleration at impact (Figure 2c).

2.3.2 Short time min-max feature

Using the specific signatures of high negative and positive peak resultant accelerations in critical phase fall signal to distinguish falls from ADL, the short time min-max feature is employed. Using a 1.5 s sliding window with 50% overlap through the resultant acceleration signal, each segment of data in the window is evaluated for minimum resultant acceleration (S_{min}) and maximum resultant acceleration (S_{max}). Examples of S_{min} and S_{max} for a 1.5 s sliding window are shown in Figure 2c. It is expected that this feature

can distinguish falls from ADL when window slides through the critical phase.

2.4 Neural network

A neural network was employed as a classifier to separate falls from ADL. The neural network in Figure 3 separates falls from ADL using a feed-forward backpropagation network (Hagan *et al.*, 1996). It is comprised of either an input node for $\max(A_{res})$ or two input nodes for S_{min} and S_{max}, one hidden layer, and an output layer. The number of nodes for each hidden layer varies between one and two nodes. The transfer functions for the hidden and the output layers are

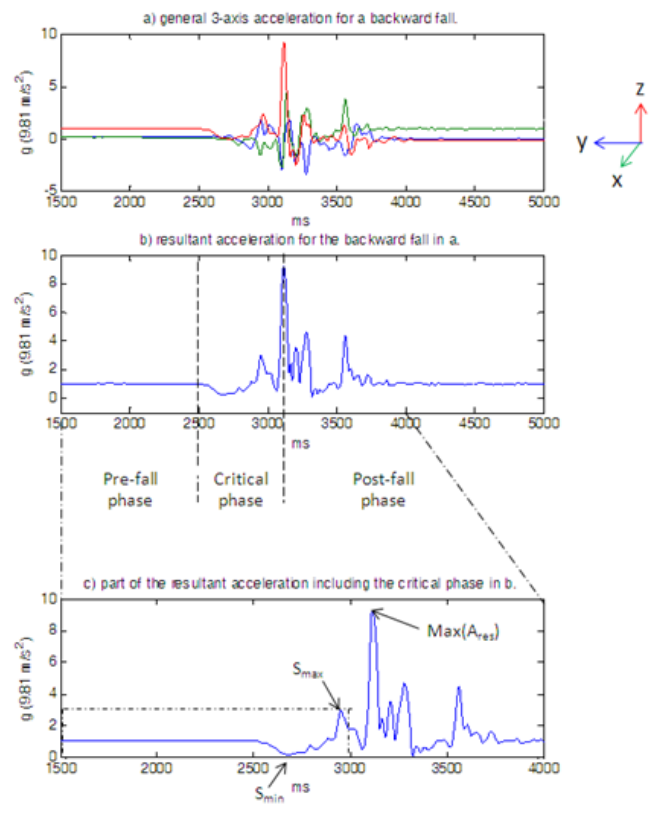Figure 1. Position of the tri-axial accelerometer.

Figure 2. a) Example of general 3-axis acceleration for a backward fall. b) Example of the resultant acceleration of the backward fall for 2a. c) Part of the resultant acceleration including critical phase of 2b and sliding window example (dash rectangle).
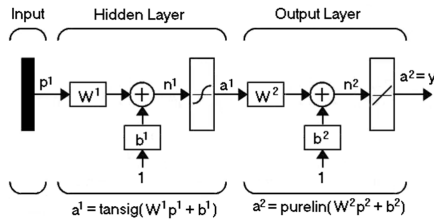
Figure 3. Two layer perceptron: feed-forward backpropagation network.

'tansig', and 'purelin'. Data are normalized for training and testing. During training, the $\max(A_{res})$ for falls are recognized as fall events, while others are recognized as non-fall events for the maximum peak feature. For the short time min-max feature, only segments involving the critical phase of falls for S_{min} and S_{max} are recognized as fall events, while others are recognized as non-fall events. For each hidden layer, three networks, which converge and display linear regression higher than 0.8, were selected for testing. A network obtained from training is shown by 'x-node' symbol, where 'x' represents a node number in the hidden layer. Outputs (for the maximum peak feature) or segment outputs (for the short time min-max feature), which are greater than 0 are detected as falls. Otherwise, they are labeled as non-falls. The outputs obtained from the three networks for each 'x-node' case were averaged for later performance evaluation.

Training and testing data were swapped for two-fold cross-validation. $\max(A_{res})$ of all the sequences, and S_{min} and S_{max} of all the segments of all the sequences, were divided into two groups for training and testing. The groups depended on the subjects, with balanced scenarios for both data groups:

1) 7 sets of young/elderly subjects were numbered 1-7,

2) 7 sets of young/elderly subjects were numbered 8-14.

2.5 Performance evaluation

There are four possible cases for fall detection:

True positive (TP): a fall occurs and the algorithm detects the fall;

False positive (FP): the algorithm declares a fall, but it did not occur;

True negative (TN): a normal (no fall) movement is performed, the algorithm does not detect a fall; and

False negative (FN): a fall occurs but the algorithm does not announce it. This event must be avoided because the elderly may receive serious injuries.

The performance is evaluated by sensitivity and specificity given by (1) and (2),

$$Sensitivity \quad (\%) = \frac{TP}{TP+FN} \times 100, \quad (1)$$

$$Specificity \quad (\%) = \frac{TN}{TN+FP} \times 100. \quad (2)$$

3. Results

3.1 Fall and ADL resultant accelerations

Even though three axes of acceleration are differently changed for all types of fall, the resultant accelerations ($A_{res} = \sqrt{(A_x)^2 + (A_y)^2 + (A_z)^2}$) still appear to be specific signatures of high negative/positive peaks in the critical phase, as shown in Figure 4 for all types of fall, i.e. forward, backward, left and right side falls. The maximum positive peaks of falls are generally several times the gravitational acceleration, and higher than those of ADL, except for soft impacts. Even though ADL resultant accelerations have positive and negative peaks like fall resultant accelerations, their positive/negative peaks are lower, as shown in Figure 5. They are usually in the interval (0.75-2 g), except for quick movements.
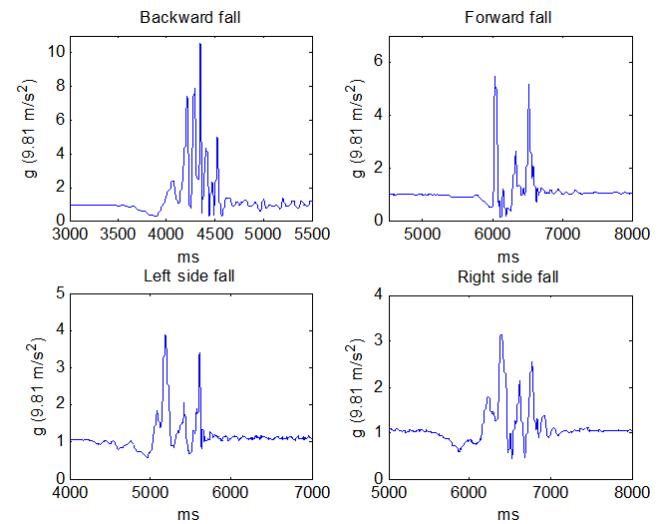

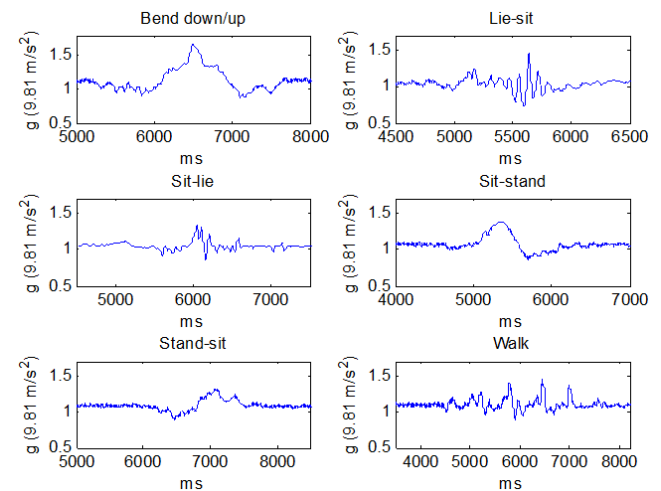Figure 4. Example resultant acceleration waveforms for different categories of fall.

Figure 5. Example resultant acceleration waveforms for different categories of ADL.

3.2 Maximum peak feature

The maximum peak for falls and ADL for the first and second data groups for Group A and B are shown as quartile box plots in Figures 6 and 7, respectively. The last character of x-label, '1' or '2', means the 'first' or 'second' data group number. The maximum peaks for the falls are usually greater than those for ADL in both data groups. However, if only a threshold is employed for the maximum peaks, several scenarios tend to overlap between falls and ADL, such as 'BF', 'LF', 'SL', and 'TS'.

3.3 Short time min-max feature

To show that S_{min} and S_{max} in critical phase can distinguish falls from ADL, scatter plots of S_{min} and S_{max} for only segments in critical phase of falls and ADL for the first and the second data groups are displayed in Figures 8a and 8b, respectively. In fact, there is no definition for critical phase of ADL. However, minimum before maximum peak is a representation of S_{min} in critical phase for ADL, and maximum peak is a representation of S_{max} in critical phase for ADL. The symbols 'red-o', 'green-*', and 'blue-x' represent data for the critical phase of falls, young ADL, and elderly ADL, respectively. These scatter plots show trends for getting better rates

of fall detection when the 1.5 s sliding window with 50% overlap slides through the critical phase of the falls.

For all segments, most of the data for young ADL and elderly ADL have low positive/negative peaks. Segment data for non-critical phase of falls have both low and high S_{min} and S_{max}, because there are several different event characteristics occurring during fall events that influence fall detection. Segments of the critical phase of falls offer very low S_{min}, which is usually lower than that from ADL, and may offer high or maximum S_{max} depending on the reach of the sliding window to the maximum peak. Also, the impacting and rebounding period in the initial post-fall phase, may offer low S_{min} and S_{max} high because of different event characteristics occurring during the fall event. Thus, the output segments of a fall sequence can be detected as a fall for segments of critical phase or segments of initial post-fall phase. However, the specific characteristics of high negative/positive peaks occur for segments involving the critical phase before initial post-fall phase, so they are first detected in the critical phase. Using feed-forward backpropagation network, '1-node' and '2-node' networks with a linear regression higher than 0.8 are employed. The first data group networks, obtained from training, were tested on the second data group, and the second data group networks, obtained from training, were tested on the first data group for two-fold cross-validation.
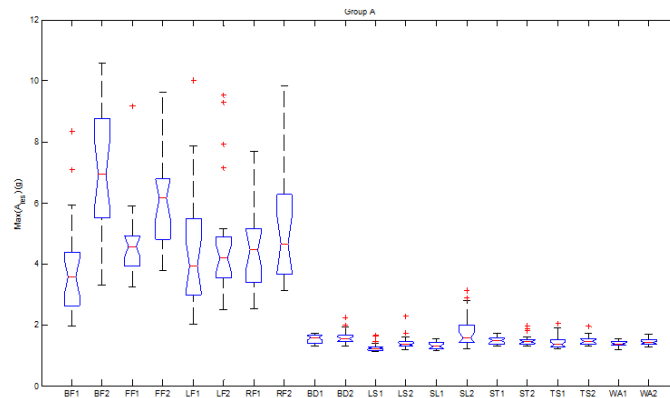

Figure 6. Quartile box plot of the maximum peak resultant accelerations for Group A.
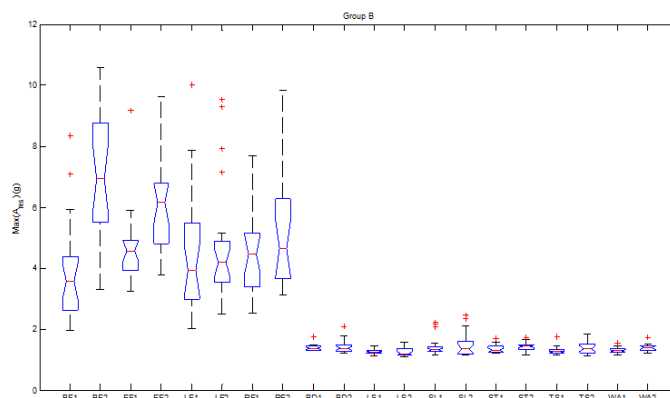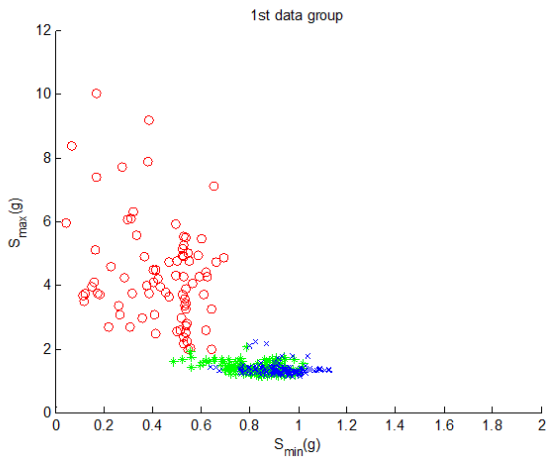

Figure 7. Quartile box plot of the maximum peak resultant accelerations for Group B.

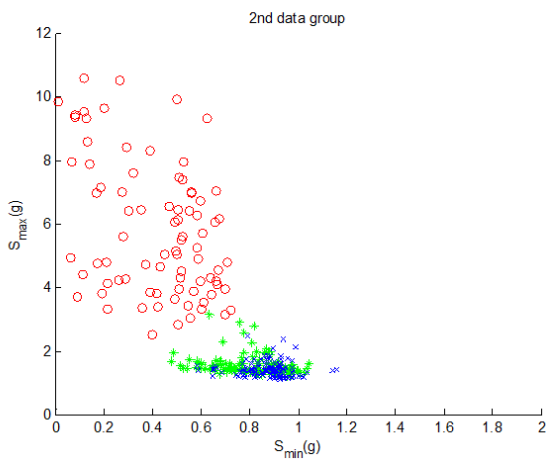a) The first data group

b) The second data group

Figure 8. Scatter plots of S_{min} and S_{max} in critical phase of falls and ADL of all sequences.

The sensitivities and specificities of each network for Group A and B are shown in Table 1 for the maximum peak feature and Table 2 for the short time min-max feature.

4. Discussion

The sensitivities and specificities of all networks for the short time min-max feature are greater than the maximum peak feature for both groups. This means that FN and FP events occurring for using the maximum peak feature are reduced for using the short time min-max feature. A FN event is unacceptable in fall detection because the elderly may receive serious injuries. Although a FP event is not a serious case like the FN event, the elderly are bothered because of inappropriate alerts.

For maximum peak feature, a number of BF, LF, and RF produce FN events, while TS and SL produce FP events for Group A. For Group B, a number of BF and SL produce FN and FP events, respectively. Examples of a FN and a FP event causing by BF and SL are displayed in Figures 9 and 10, respectively. A cause for FN events is a soft impact, which gives a maximum peak like that from ADL. These FN events, however, can be reduced by the short time min-max feature because a negative peak in a critical phase can distinguish falls from ADL. A cause for FP events of SL and TS is a body movement producing a maximum peak like that from falls, because a body sometimes impacts a mattress/chair with acceleration greater than general. Although these cases produce high maximum peaks, they do not usually produce high negative peaks because of slow movement at a beginning of a descent onto a mattress/chair. Thus, these cases can be reduced for Group A and completely deleted for Group B by the short time min-max feature.

For comparison between the result from the maximum peak and the short time min-max feature for both subject groups, the sensitivities and specificities for both features

Table 1. The sensitivities and specificities of each network for the maximum peak feature for both groups.

Network	Group A		Group B	
	Sensitivity	Specificity	Sensitivity	Specificity
1-node	97.0	98.4	97.6	98.7
2-node	96.2	98.4	97.8	98.5

Table 2. The sensitivities and specificities of each network for the short time min-max feature for both groups.

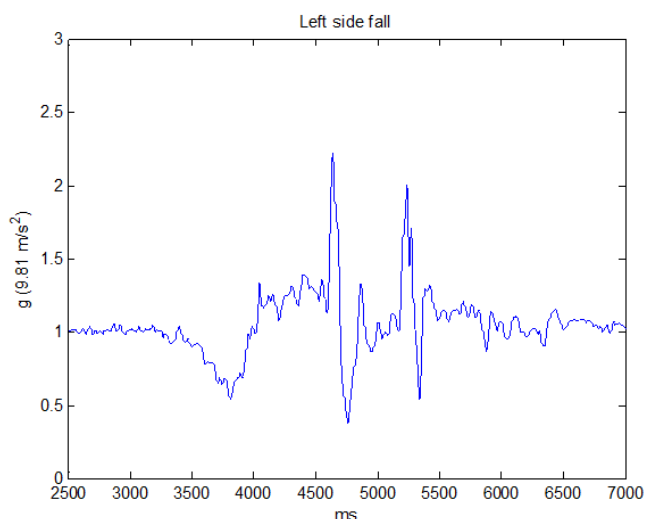| Network	Group A		Group B	
	Sensitivity	Specificity	Sensitivity	Specificity
1-node	98.2	99.3	99.4	100.0
2-node	98.0	99.3	99.2	100.0

Figure 9. An example of a left side fall producing FN for the maximum peak feature.
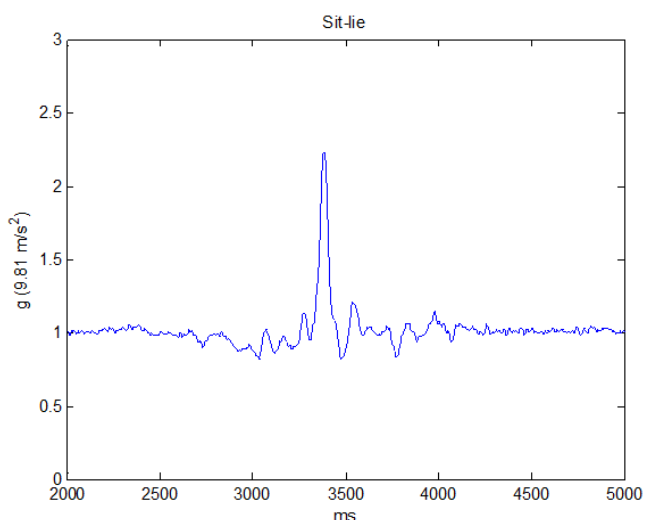

Figure 10. An example of a sit-lie producing FP for the maximum peak feature.

for Group B are greater than that for Group A for all networks. The results indicate that it is easier to distinguish falls in the young from elderly ADL than to distinguish falls in the young from young ADL, like our previous studies (Jantaraprim *et al.*, 2009). This is due to the fact that the speeds of movements in the young are faster than those in the elderly. Therefore, the maximum peak feature, or the high positive/negative peak for the short time min-max feature of some young ADL are greater than those from the elderly, and sometimes are similar to those from falls. Therefore, these characteristics tend to produce more FP events. In addition, some young ADL movements, which produce maximum peak like soft impact falls, make it more difficult to establish a valid decision for the classifier. Thus, some falls with lower maximum peak than general produce FN events.

The results also show that the proposed system consisting of the short time min-max feature and the feed-forward backpropagation network can improve the fall detection performance despite in the case of distinguishing falls from young ADL, which is more difficult than distinguishing falls from elderly ADL. The short time min-max feature offers the better performance for both subject groups.

5. Conclusions

We propose improving fall detection performance for different subject groups using a short time min-max feature based on the specific signatures of critical phase fall signal and a neural network as a classifier. The performances were evaluated by a feed-forward backpropagation network, which varies between one and two nodes in a hidden layer. Three networks with linear regression higher than 0.8 for each network case were employed to find the sensitivity and specificity. Two different subject groups were performed: Group A considered falls and ADL by young subjects, while Group B studied falls by young subjects and ADL by elderly subjects. The results show a performance comparison between the maximum peak and the short time min-max feature. For tests involving 672 sequences, we found that the short time min-max feature offers the performance better than that from the maximum peak feature for both different subject groups and all networks. One node in the hidden layer is enough for fall detection. The short time min-max feature, 1-node network, offers the best performance for both subject groups, which is 98.2% sensitivity and 99.3% specificity for Group A, and 99.4% sensitivity and 100% specificity for Group B. The sensitivities and specificities for both features for Group B are greater than those for Group A for all networks. Not only improving fall detection performance for both different subject groups, the short time min-max feature based on the specific signatures of critical phase fall signal gives better performance using only one sensor on a body's position, without a fixed threshold for 100% sensitivity or specificity and does not involve additional processing for posture after a fall.

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