Evaluation of Fall Detection for the Elderly on a Variety of Subject Groups
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ABSTRACT
Falls in the elderly are a major problem for today’s society. If the elderly could get help immediately after the fall, the severity of the injury could be reduced. Also, it results in decreasing the rate of death and the medical cost. This paper presents a fall detection algorithm based on the threshold value of the maximum peak resultant acceleration to classify falls and Activity of Daily Live (ADL). Two types of the experiments were investigated. Type A) ten young subjects performed both falls and ADL. Type B) ten young subjects performed falls whereas ten elderly subjects performed ADL. In the experiment, tri-axial accelerometer was mounted on the trunk. There were four categories of falls: forward fall, backward fall, left and right side fall and six categories of ADL: sit-stand, stand-sit, sit-lie, lie-sit, bend down, and walking 2 m. For the threshold of the maximum peak resultant acceleration at 1.9g, falls could be distinguished from ADL with 100% sensitivity in both Type A and B while specificity for Type A and B were 96.11% and 98.33%, respectively. Results indicate that the trend in classification of fall from ADL in the elderly could gain the increase in error. Therefore, more sophisticated algorithms for the classification of fall from ADL in the elderly are needed to improve performance of detection.

Categories and Subject Descriptors
C.3 [Special-purpose and application-based systems]: – Real-time and embedded systems.

General Terms
Algorithms, Design, Experimental

Keywords
Fall detection, accelerometer, the elderly

1. INTRODUCTION
The improvement in medical technologies for health and the decrease in the rate of birth result in increasing the population of the elderly. One important problem often found in the elderly is falling. Jitapunkul [1] reported that 4,480 Thai elders at the age of 60 and over had a falling incident within the last 6 months 18.7% on average (male 14.4%, female 21.5%). Often, the falls occurs outside. Although most of the falls cause minor injury but there also be long term effects. The major problem caused by falls is hip bone fracture due to bone thinning, which already exists in the elderly. It is found that the elderly at the age of 65-69 have hip bone fractures one out of two hundred falls. In addition, this rate increases when the age increases. Apart of that, if the fall results in head trauma, it might lead to partial or full paralysis. If the elderly can get help immediately after the fall, the severity of the injury can be mitigated. It also results in decreasing the risk of paralysis and death.

Most studies in fall detection algorithm were usually carried out using a threshold value from the maximum peak resultant acceleration. Other parameters such as the change in orientation [6] or posture detection after the fall [5] are also investigated. Bourke’s studies [3]-[4] used a single threshold of the resultant-magnitude acceleration signal from a tri-axial accelerometer located at the trunk. For ten young male and ten elderly in his studies, the performance could be achieved 100% both in sensitivity and specificity. However, only fall in the young was classified from ADL in the elderly. Although various falls and ADL were performed in his studies, the elderly often move differently compared to younger people as they typically have less control over the speed of their body movements. Some studies used threshold from the maximum peak resultant acceleration as main method to detect falls and only young subjects perform both falls and ADL [5]-[7]. These studies also obtain high performance. However, the number of subjects is not high (not exceed 5 subjects) and the categories of ADL were not various. Even though no study has used elderly subjects to perform the simulated falls because of moral reasons, the effects of using different subject groups to perform falls are still attractive to investigate. This paper presents the comparison of fall detection using the threshold value of the maximum peak resultant acceleration from a variety of subject groups and activities to perform falls and ADL. Tri-axial accelerometer mounted at the trunk was used to detect falls and ADL. While ten young subjects performed both falls and ADL, ten elderly subjects performed only ADL. The rest of paper is organized as follows. Section 2 describes materials and method. Section 3 presents the results. Discussion and conclusion are given in Section 4.
2. MATERIALS AND METHOD

2.1 Experimental Setup

![Block diagram of system.](image1)

Figure 1. Block diagram of system.

![Position of accelerometer at the trunk.](image2)

Figure 2. Position of accelerometer at the trunk.

Figure 1 shows the block diagram of the system used for data acquisition. Two dual-axis MEMS accelerometers (Analog Devices ADXL321) were mounted at right angles to each other in order to measure three orthogonal axes of acceleration. Position of the accelerometer at the trunk was shown in Figure 2. The signals from each axis were processed by a second-order low-pass Butterworth digital filter with a cut-off frequency of 20 Hz. These signals were calibrated to generate acceleration signals. Data were acquired with 12-bit resolution at 1-kHz sampling frequency. Subsequently, data were recorded and saved for offline processing by a computer.

2.2 Subjects

In the experiment, the subjects were divided into 2 groups:

1) Ten young subjects (7 male and 3 female, age 27.3 ± 4.6 years, body mass 63.8 ± 11.2 kg, and height 169.6 ± 7.7cm)

2) Ten elderly subjects (7 male and 3 female, age 69.7 ± 4.3 years, body mass 63.3 ± 10.3 kg, and height 161.6 ± 9.4cm).

To compare the results of detection tested by a variety of subject groups to perform falls and ADL, the experiments were divided into 2 types:

- **Type A**: Young subjects performed both ADL and simulated falls.
- **Type B**: The young subjects in Type A performed simulated falls whereas the elderly performed ADL.

Four categories of falls performed on the large crash mats are composed of forward fall (FF), backward fall (BF), left (LF), and right (RF) side fall. Six categories of ADLs were performed with normal speed in their familiar environment, including sit-stand (ST), stand-sit (TS), sit-leaf (SL), lie-sit (LS), bend down (BD), and walking for 2 m (WA). Each scenario was repeated 3 times for each subject. Therefore, total data were 300 sequences (120 fall data and 180 ADL data).

2.3 Fall Detection Algorithm

After all acceleration signals in three axes were acquired, they were converted to the resultant acceleration by

\[ A_{\text{res}} = \sqrt{A_x^2 + A_y^2 + A_z^2}, \]

where \( A_{\text{res}} \) was the resultant acceleration of tri-axial accelerometer. \( A_x, A_y, \) and \( A_z \) were acceleration in x, y and z axis, respectively. The threshold value based on the maximum peak resultant acceleration was used for classifying falls and ADLs in two types of data, i.e. type A and type B from the experiment.

2.4 Performance Evaluation

The sensitivity and specificity were used to evaluate the performance [2]. There are 4 possible cases for fall detection:

- True positive (TP): A fall occurs and the algorithm detects the fall.
- False positive (FP): An ADL movement is performed but the algorithm detects it as a fall.
- True negative (TN): An ADL movement is performed and the algorithm detects it as the ADL.
- False negative (FN): A fall occurs but the algorithm detects it as an ADL.

Based on TP, FP, TN, FN values, sensitivity, i.e. the capability to detect a fall, can be expressed as

\[ \text{sensitivity} = \frac{TP}{TP + FN}, \]

and specificity, i.e. the capability to detect an ADL, is given by

\[ \text{specificity} = \frac{TN}{TN + FP}. \]

3. RESULTS

Figure 3 shows example waveforms of the resultant accelerations from six categories of ADLs and four categories of falls. We can clearly see that generally the maximum peaks of resultant acceleration from falls are higher than those from ADLs. As a quantitative measurement, an example of resultant acceleration waveform acquired from backward fall is shown in Figure 4. The maximum peak of resultant acceleration is 9g, which is much higher than those from ADLs shown in Figure 3.

The maximum peak of resultant accelerations of total data from Type A and Type B are shown with quartile box plots in Figure 5 and Figure 6, respectively. All falls from both experimental types
are detected when the threshold value of the maximum peak resultant acceleration is set at 1.9g ($FN=0$). As a result, the sensitivity values of both types are 100%. Although most ADLs are distinguished from falls for Type A and B, there are some false positives for both types. Seven false positives of Type A were produced by all ADLs whereas three false positives of Type B were produced by sit-stand. As a result, the specificities of Type A and B were 96.11% and 98.33%, respectively.

![Figure 3. An example of resultant acceleration waveforms from six categories of ADLs and four categories of falls (BD: bend down to pick up the object, LS: lie-sit, SL: sit-stand, TS: stand-sit, WA: walking 2 m, BF: backward fall, FF: forward fall, LF: left side fall, and RF: right side fall).](image)

![Figure 5. Quartile box plot of the maximum peak resultant acceleration of Type A.](image)

![Figure 6. Quartile box plot of the maximum peak resultant acceleration of Type B.](image)

4. DISCUSSION AND CONCLUSIONS

We present and compare results of fall detection algorithm based on a threshold value from the maximum peak of resultant acceleration. Two types of data are investigated. While in Type A data the classification of fall and ADL in the young is performed, in type B data the classification of fall from the young and ADL from the elderly is carried out. At the threshold of 1.9g we can achieve 100% sensitivity from both types. That is, all falls from both types of data are correctly detected when the threshold is 1.9g. On the other hand, the specificity from Type A and Type B are 96.11% and 98.33%, respectively. In other words, seven ADLs are detected as falls in Type A and three ADLs are detected as falls in Type B. Our accuracy is slightly different from other publications, which can get 100% correctly detection because we carry out experiment with more subjects. Therefore, we have greater variations in data.
Moreover, accuracy of Type B classification is better than that from Type A. This indicates that it is easier in the classification of fall in the young from ADL in the elderly compared to the classification of fall in the young from ADL in the young. This is due to the fact that the speeds of movements in the young are faster than those in the elderly. Consequently, the maximum peak resultant acceleration of ADL for each scenario in the young is higher than that from the elderly. This observation is confirmed by median and mean values resulting from experimental data shown in Figure 7 and Table 1. Due to this difference in maximum peak resultant accelerations of ADL, classification rate, i.e. specificity, of the fall and the ADL in Type B is higher than that from Type A.

For reliable operation of the fall detection system, fall events should not be missed while false positives should be minimized. A good way to protect false alarms is that we should add other algorithms to provide better classification between fall and ADL data. The algorithm should employ the characteristic of signal waveform both in time and frequency domains, which is ongoing research. Results will be reported in the near future.

5. ACKNOWLEDGMENTS
We are grateful to PSU scholarship for supporting us to do this research. In addition, this work is partially supported by NECTEC-PSU center of excellence for rehabilitation engineering.

6. REFERENCES