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Enhancement of Fall-Detection Rate using Frequency Spectrum Pattern Matching

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ABSTRACT

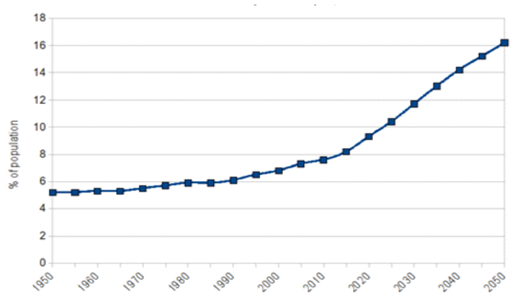
To the elderly, sudden falls are one of the most frightening accidents. If an accident occurs, a prompt action has to be taken to deal with the situation. Recently, there have been a number of attempts to detect sudden falls using acceleration sensors embedded in the mobile devices, such as smart phones and wrist-bands. However, using the sensor readings only, the detection rate of the falls is around 65%. Ordinary daily activities such as running or jumping could not be well distinguished from the falls. In this paper, we describe our attempts on improving the fall-detection rate. We implemented a wrist-band fall detection module, using a three-axis acceleration sensor. With the pattern matching on the fall signal-strength frequency spectrum, in addition to the conventional signal strength measurement, we could improve the detection rate by 9% point. Furthermore, by applying two wrist-bands in the experiment, we could further improve the detection rate to 82%.

☞ keyword : Fall detection, Acceleration measurement, Frequency spectrum, Pattern matching

1. Introduction

Because of better healthcare services, the life expectancy of Korean society is increasing. According to the 'future population estimates 2014' of Korea National Statistical Data Portal, proportion of the elderly aged over 65 is 12.7%. Korea had already entered the 'Aging Society' in 2000, and will be in the 'Aged Society' in 2018, where the population over 65 years old becomes 14.3%. It is expected to reach a 'super-aged society' with the elderly population of 20.8% in 2026[1].

As we see from Figure 1, the aging is progressing world-wide. Elderlies are exposed to various accidents compare to other age groups. Sudden falls are one of the most common and dangerous accidents they may face with.



(Figure 1) UN World Population Prospect, 2008

According to a survey, annual fall rate of over 65 years of age was reported 28~30%, over 70 years of age was about 35%, over 75 years of age was about 32~42% and over 80 years of age was about 50%[2]. Elderly falls may result in a physical damage as well as a psychological damage caused by dysfunction. In the worst case, one could die because of the accidents and the complications associated with. For the reason, a number of studies have been performed to detect falls of the elderly.

Method for determining falls can be classified roughly into two types: 1) utilizing images 2) using the readings from sensors attached to the body. However, use of the image is a sensitive matter due to privacy issue, so the use of the sensor is more common.

Earlier studies measure acceleration signals of one or two directions, attaching a single or two-axis acceleration sensors

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to some part of the body. By using the sensor reading values, they distinguish various movements. For example, T. Zhang proposed a method for attaching an acceleration sensor to torso to detect a fall. He then proposed a new method, which mounts acceleration sensor to a mobile phone. However, this method has a major defect, because it assumes that one holds a smart phone when a sudden fall occurs [3].

Recently, attempts to attach sensors at various locations of the human body such as waist or chest are made to detect various postures and activities of the human. Wrist watch type wearable devices give comfort, but they have low fall detection capability because of free movement of the wrist. For example, T. Degen determined a fall by calculating the norm through the three-axis acceleration integration, but the detection average rate was only around 65% [4].

This study implements a fall detection module, as a small wrist-band, using a three-axis acceleration sensor. We used an algorithm of [5, 6] to recognize the fall. It uses magnitude of the signals which are measured by the acceleration sensors. However, in addition to the conventional approach, we augmented a pattern matching technique in order to improve the fall detection rate. To make the system more practical, notification of the fall is to be made immediately to the predefined emergency contacts automatically. Furthermore, we have experimented our new approach with two wrist-bands of the same type, and found that fall detection can be significantly improved.

The rest of the paper is organized as follows: In Chapter 2 we look at the characteristics of the acceleration sensor used for the fall detection. We also describe the structure of the application, algorithm used for the fall detection, and the notification mechanism. In Chapter 3, we describe the overall structure of the fall detection system and details of the fall detection experiments. Chapter 4 analyzes the experimental results and looks at the possible future researches, and concludes.

2. System Components (H/W and S/W)

2.1 Acceleration Sensor

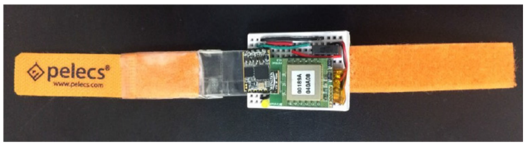
In this study, we use an acceleration sensor (EBIMU-9DOFV2) to detect the fall. This module is a small AHRS (Attitude Heading Reference System) module, which has a three-axis acceleration sensor, a three-axis gyroscope, and a geomagnetic sensor. Among these sensors we use the acceleration sensor to acquire the fall related data. The sensor produces output rate up to 1000Hz, eliminating the gravitational effect. For a stable output acquisition, we set the output rate 50 times per second. It supports ASCII output mode, Hex (binary) output mode, and polling mode. We use ASCII output mode for an easy data manipulation as shown in Figure 2. Operating power of the sensor is 4.5V. A digital low pass filter (50 ~256Hz) is installed in the sensor in order to remove noise. The size of the module is quite small so that it can be composed as a wrist-band.

SOL	DATA 1	sp	DATA 2	sp	...	sp	DATA n	EOL
*	ascii data 1	,	ascii data 2	,	...	,	ascii data n	CR LF

(Figure 2) ASCII Data Format

2.2 Fall Detection using an Acceleration Sensor

In this study, we developed a fall detection band to detect falls as in Figure 3. The band is composed of an acceleration sensor (EBIMU-9DOFV2), a bluetooth module (FB-744AS), and a lithium ion polymer battery. We tried to cut down the size of the wearable device to minimize the interference with ordinary daily activities.

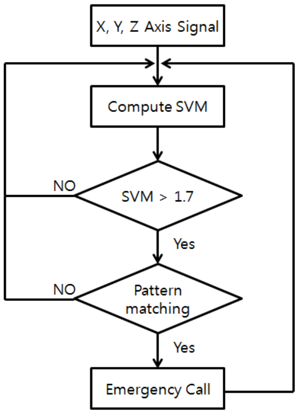


(Figure 3) Fall detection band

2.3 Android App

We also developed an Android app in order to detect the fall using the acceleration values from the wrist-band. In addition, the app acts as a gateway for emergency notification. Consideration for the elderly, who are to be the primary users of the app, is made, so that we tried to make the user interface as easy as possible. We minimized the complicated set-up,

(Figure 4) GUI of the App



(Figure 5) Algorithm flow chart

and gave an intuitively manageable GUI as in Figure 4.

With the app, a user may turn on/off the fall detection functionality, register telephone numbers that are to be used for emergency notification. It also provides useful information about the fall prevention and the app usage.

2.4 Fall Detection Algorithm

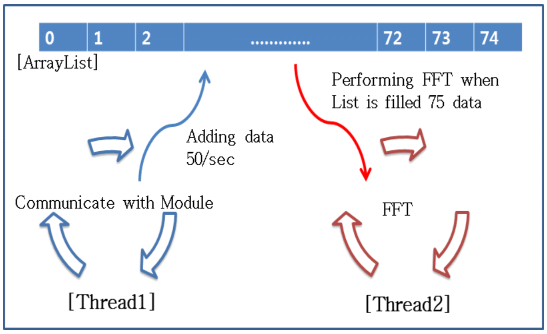
To determine a fall, we follow the logical flow shown in Figure 5. First, we determine the fall with SVM value above 1.7g (g is the gravitational acceleration constant 9.8m/s^2). SVM is a popular formula for determining falls using a 3-axis accelerometer. However, in this study, we improved the fall detection ratio with frequency pattern matching on the fall signals. SVM is used by several researchers to detect falls [5, 6]. The SVM formula is as follow:

$$SVM = \sqrt{x_i^2 + y_i^2 + z_i^2} \tag{1}$$

x_i is an acceleration signal between forward and rear direction, y_i is acceleration signal between left and right direction, z_i is an acceleration signal between top and bottom direction. Several studies reported that value of SVM is above 1.8g when a fall occurs [7, 8, 9, 10]. In order to verify the value, we have performed a repetitive experiments to detect the value. We found the best approximation SVM value for the fall detection is 1.7g. We think this is due to the characteristics of the acceleration modules. Therefore, we assume the fall, when the SVM value is above 1.7g.

However, the detection precision of SVM is about 65%. We cannot often distinguish a fall with other normal activities such as jumping and running. Therefore, in order to improve the fall detection precision, we suggest applying frequency pattern matching to the falls.

In this study, we define a pattern in terms of the frequency spectrum of falls. We perform FFT (Fast Fourier Transform) to see the spectrum of a movement which has the SVM value 1.7g or above. Before performing the FFT, we sampled the acceleration data in a 0.02 second interval and calculated SVM values. The sampling duration is set to 1.5 seconds, which we conjecture it as a fall motion duration. With the interval, we could measure 75 SVM values for every 1.5 second duration as it is shown in Figure 6. We used the series of SVM values to represent a fall motion. We expected, some frequency patterns will be discernable when a fall occurs. The experimental results will be described in Section 3 in detail.

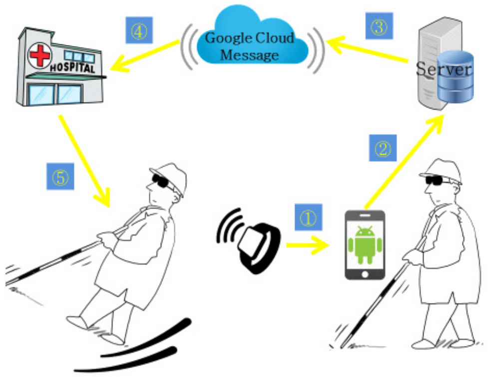


(Figure 6) Pattern building from SVM values

2.5 Other Parts of the System and their Integration

The fall detection module proposed in this study consists of a wrist-band and an Android app. The operational scenario of the system is shown in Figure 7. Signals obtained from the wrist-band sensors are given to the smart phone associated with. If the fall detection algorithm detects a fall, a push message from the app is sent to the pre-registered numbers.

GCM (Google Cloud Message) is Google's push message service that allows developers to transfer data from a server to their Android applications. Usually, it is used to provide short data to the apps. In this study, we implemented an emergency notification mechanism using GCM, so that once a fall is detected, a push message is delivered to the pre-registered telephone numbers.



(Figure 7) System Scenario Experimental Results and Analysis

3. Experimental Results and Analysis

In order to improve the fall detection rate, we performed various experiments to find the characteristics of the fall signal spectrum. 20 volunteers between 20-30 years of age, regardless of gender, are selected as experimental targets. They do not have problem with ADL (Activities of Daily Living) and no problem in walking. Table 1 summaries the information of the participants. Experiments are made on the daily activities such as walking, running, sitting, etc. Seven activities are compared one another as shown in Table 2. For each activity, we have performed 20 experiments to get better approximation values.

(Table 1) Information of volunteers

Sex	N	Age	Height(cm)	Weight(kg)
Male	13	23.8±1.9	172.8±2.9	69.5± 9.5
Female	7	21.7±1.4	162.2± 4.9	55.6± 8.2

(Table 2) ADL experiment list

Motion	Explanation
Walking	Walking on a flat floor around 30m
Running	Running on a flat floor around 30m
Climbing stairs	Climbing stairs for 60 seconds
Sitting	Sitting and standing: Repeat for 10 seconds
Laying	Laying and standing: Repeat for 10 seconds
Standing jump	Standing jump
Fall	Falling motion (forward, rear, left, and right)

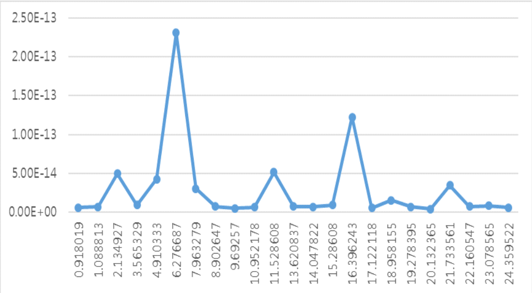
With the acceleration sensor data acquired, we first tried to find the SVM threshold value for the fall. We found it 1.7g ($g=9.8m/s^2$). However, with this value, behavior such as running, climbing stairs could not be distinguished from the fall as shown in Table 3. In order to better distinguish the actions, we have performed FFT (Fast Fourier Transformation) on the changing SVM values. Results gotten from the FFT on different actions are shown in Figure 8 through Figure 10. For running and climbing stairs, we found, particular frequency bands are dominant. In the case of a 'standing jump', more than 20Hz frequency bands are generated. For the fall, below 3 Hz frequency bands were dominant. With this distinctive characteristics, we could determine the fall more precisely. Our experiments gave us 74% detection rate.

In addition to this new approach, we have experimented the fall detection with two wrist-bands applied on each wrist. The reason why we did this was that if a fall occurs on one direction (left or right), it may not give enough movement for detection.

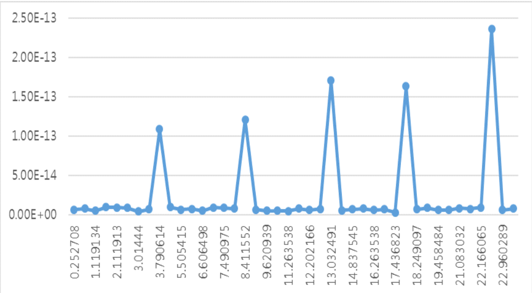
With 220 fall trials, we could detect 181 cases, which give us 82% detection rate. We assumed a fall when either one of the sensor detects the fall according to our algorithm.

(Table 3) SVM Min/Max average value

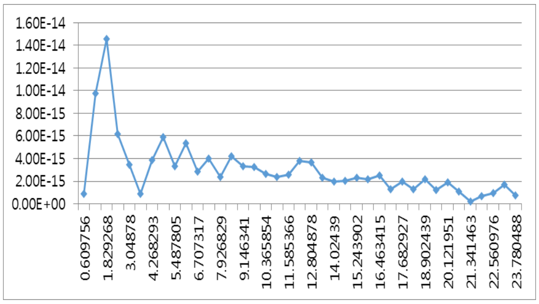
Motion	Average Min SVM Value	Average Max SVM Value
Walking	0.66±0.18	1.53±0.2
Running	0.40±0.26	2.79±1.43
Climbing stairs	0.66±0.12	1.72±0.20
Sitting	0.18±0.09	4.56±1.25
Laying	0.64±0.15	1.61±0.32
Standing jump	0.55±0.17	1.57±0.37
Fall	0.19±0.09	5.17±3.31



(Figure 8) Frequency bands of 'Running'



(Figure 9) Frequency bands of 'Climbing stairs'



(Figure 10) Frequency bands of 'Fall'

4. Conclusion

A fall is a serious threat to the elderly. Although it is best to prevent the falls, in reality, they are inevitable. However, when an accident occurs, if we take appropriate follow-up actions promptly, we may better deal with the situation so that the elderly may be able to escape quickly and safely from various risks.

In this paper, we proposed a system that can detect the fall and notify the accident to appropriate contact points such as guardians or an emergency center.

This study is not the first one to do this, but the fall detection rate has improved by using the frequency spectrum pattern matching we have suggested. The fall experiment was performed in the directions of front/rear/left/right for 20 times each. With the new algorithm, we could detect the fall 59 time out of 80. In fact, by applying this technique, we could improve the detection rate from 65% to 74%. Furthermore, by applying two wrist-bands, we could further enhance the detection rate to 82%. This result is gotten from 220 fall trials.

The fall determining algorithm proposed can be summarized as follows: 1) Convert the signals of the acceleration sensors and calculate the SVM value. 2) If the value is more than the threshold (1.7g), classify the action as a candidate fall. 3) Perform FFT on the SVM values of 1.5 seconds interval (70 samples). 4) Compare the dominant frequency pattern of the action. From the experiment, we found that for the 'Standing jump', 20Hz or higher frequency bands are mainly generated. In the case of the 'fall', below 3 Hz frequency band was noticeable. In other words, when the SVM is above 1.7g, and the frequency spectrums below 3 Hz are dominant, we consider it as a fall.

In the future, we are going to improve the fall detection rate by applying other sensors to the system. We also would like to use the system to identify different daily actions, so that we may use the data for monitoring and analyzing personal living pattern of the people.

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