# Fall detection system via smart phone and send people location

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***Abstract*—Due to the falling birth rate and industrial societies, the number of people over 65 is increasing and in 2050 almost 16% of the population will be elder. Falling in the elderly is the second leading cause of severe injury, leading to death. The aim of this study is to provide a high-speed method for diagnosing and treating the elderly. We have proposed a method to use the smartphone and the acceleration signal to detection falling. The proposed system has been able to detect a fall using the Smartphone sensor and report the location of the person. The results show that with the mean, skewness, and kurtosis features and support vector machine classifier, the accuracy of fall detection is 96.33%. The important point is the calculation time, which is less than 1 second.**

**Keywords—mobile health; fall detection; classification; feature extraction**

## I. INTRODUCTION

With the world's aging population, health-enabling technologies and ambulatory monitoring of the elderly has become a prominent area of multi-disciplinary research [1,2]. The population of the elderly today is growing, especially in developed or developing societies, and research has also confirmed this fact [3]. Researchers have also been able to provide an estimate of the growing population in the coming years. By 2050, nearly 16% of the world population will be 65 years of age and older, which is 2.5 times more than in 2010 [4]. According to Statistics Canada, more than 62% of the elderly and patients are physically related to falls [5]. Also, 30% of people over the age of 65 living alone at home have a fall accident each year, with 20% of these falls requiring medical care [6]. So falling can be one of the biggest causes of elderly people's physical injuries that seriously threaten them. It is clear that after falling, one may not be able to ask or return to normal and the likelihood of injury is increased, so prompt and timely detection can be extremely important. Wearable device applications have gained incredible popularity in many areas of daily life, such as health entertainment, communication, rehabilitation and education [7]. Nowadays, everyone has smartphones, and fortunately they are always available. Smartphones have many sensors such as accelerometer, gyroscope, GPS system. Using these facilities can help people in their lives. Threshold-based methods are one the most popular techniques for fall detection using wearable sensors.

## II. MATERIAL AND METHODE

### A. System Design

There are five main task in this study, as shown in figure1.the first one is collect data and in this part, we create dataset with 18 volunteers with 3520 records. Dataset collect from iPhone 7+. second part, we survey a data for missing data. at the third part we extract a feature from preprocessed data. at the fourth part, we have a classification process and in fifth part our system decide to active emergency mode Or continue to record the signal.

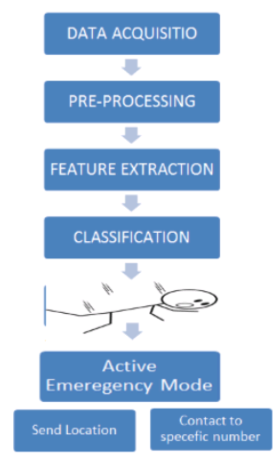


Figure 1 : main flowchart of proposed method

### B. Dataset

Eighteen healthy men and three healthy women have participated in this test. They were asked to put their smartphones in the front pocket of their pants. Before the test, participants are given a description of the test. Table 1 shows the specifications of the participants in this test. We collected data while walking, sitting, sleeping, lying down, getting up, and falling.

### C.Experimental :

The propose system using iPhone 7+ running IOS 12.0.1 .accelerator/gyroscope that report 3-axis acceleration measures(i.e.,ax,ay,az), and 3 – axis angular rate . the system calculate acceleration as $\sqrt{(ax)2 + (ay)2 + (az)2)}$ . figure 2 shows an example fall.

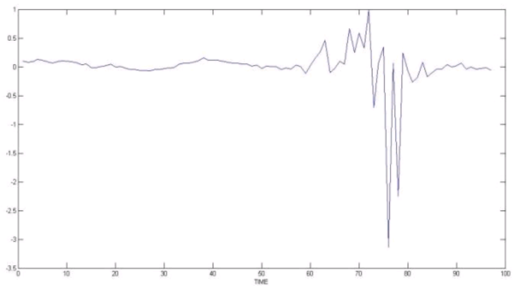


Figure 2 : fall acceleration example

D..Feature extraction :

Raw data is not useful for us . for discover the pattern of each activity and make discrimination , we should extract a feature from raw signal . From each activity we extract this feature :

$$\text{Mean(d)}:\mu=\frac{1}{N}\sum_{i=1}^{N} d_i \quad (1)$$

$$\text{Variance(d)}:\sigma^2 = \frac{1}{N}\sum_{i=1}^{N}(d_i - \mu)^2 \quad (2)$$

$$\text{Sleekness(d)}:\frac{1}{N\sigma^3}\sum_{i=1}^{N}(d_i - \mu)^3 \quad (3)$$

$$\text{Kurtosis (d)}:\frac{1}{N\sigma^4}\sum_{i=1}^{N}(d_i - \mu)^4 \quad (4)$$

$$\text{Autocorrelation(d)}:R_{ss}(\Delta) = \frac{1}{N-\Delta}\sum_{i=1}^{N-\Delta-1}(d_i - \mu)(d_{i-\Delta} - \mu),\Delta=0,1,\ldots,N-1 \quad (5)$$

$$\text{DET(k)}=\sum_{i=0}^{N-1} d_i e^{-j2\pi ki/N},k=0,1,\ldots,N-1 \quad (6)$$

To create the final feature vector, we used the SFS algorithm [8] to select the optimal features. In this system, speed and accuracy are very important, and we tried to have the highest speed with the least features.

$$\text{Accuracy}=\frac{(TP+TN)}{TP+TN+FN+FP}*100\% \quad (7)$$

$$\text{Sensitivity} = \text{TPR} = \frac{TP}{TP+FN} * 100\% \quad (8)$$

$$\text{Specificity} = \text{TNR} = \frac{TN}{TN+FP} * 100\% \quad (9)$$

where: TP = True positive; FP = False positive; TN = True negative; FN = False negative

Table 2 : the result of Classification

| Classifier | Accuracy | Specificity | Senility |
|---|---|---|---|
| SVM | 96.33% | 96.22% | 95.89% |
| Random forest | 89.36% | 90.49% | 88.76% |
| Decision Tree | 91.54% | 92.17% | 90.97% |

STD=2%

Table 1 – volunteers feature

| | Men | | | | | | | | | | | | | | | Women | | | ALL |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| volunteers | 1001 | 1002 | 1003 | 1004 | 1005 | 1006 | 1007 | 1008 | 1009 | 1010 | 1011 | 1012 | 1013 | 1014 | 1015 | 1016 | 1017 | 1018 | - |
| Ages | 21 | 25 | 22 | 30 | 20 | 22 | 22 | 28 | 18 | 19 | 18 | 25 | 26 | 22 | 23 | 31 | 29 | 27 | 23.77 |
| Height(kg) | 70 | 81 | 72 | 83 | 61 | 55 | 49 | 55 | 51 | 56 | 61 | 70 | 53 | 49 | 63 | 49 | 52 | 55 | 60.27 |
| Weight(cm) | 170 | 165 | 180 | 176 | 160 | 175 | 184 | 170 | 157 | 159 | 171 | 172 | 176 | 169 | 168 | 169 | 168 | 168 | 169.83 |

When a person falls to the ground, we have designed system that uses GPS to send the position of the injured person to the person's relatives or the nearest emergency center via SMS. The position of injured people can also be sent via SMS and via email to any person. for example, one person with ID 1003 falls on ground and the system report a location [36.3083101500757, 59.5850440759303]. Figure 2 shows the position of the injured person using Google Maps. The system detects the person falling, makes a pre-recorded call, and reports the person's location.

## III. COUNCLUSION

Smartphones play a significant role in our lives today. In this study, a method for rapid diagnosis of fall was proposed. The acceleration signal was recorded using a smartphone from 18 healthy individuals and various features were extracted from it. Previous studies have shown that not all features are useful, and in this study, speed in diagnosis is very important. The SFS algorithm has a higher speed than metaheuristic algorithms. The results show that with the mean, skewness, and kurtosis features and support vector machine classifier, the accuracy of fall detection is 96.33%. The important point is the calculation time, which is less than 1 second.

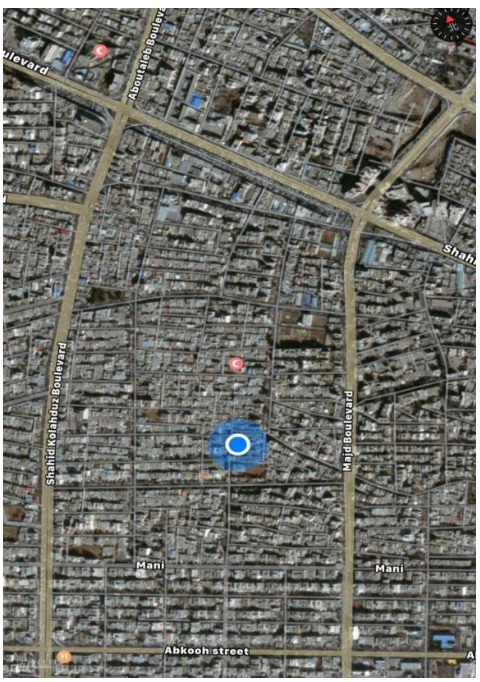


Figure 3 : location of person

[36.3083101500757, 59.5850440759303]

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