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The Novel Fall Detection and Prevention Algorithm for Elderly People

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Abstract: Falls are dangerous for the elderly population; therefore, many fall detection systems have been developed. However, previous methods are bulky for elderly people or only use a single sensor to isolate falls from daily living activities, which makes a fall difficult to distinguish. In this paper, we present a cost-effective and easy-to-use portable fall-detection sensor and algorithm. Specifically, to detect human falls, we used a three-axis accelerator and a three-axis gyroscope in a mobile phone. We used the Fourier descriptor-based frequency analysis method to classify both normal and falling status. From the experimental results, the proposed method detects falling status with 96.14 % accuracy.

Keywords: u-health, Fall detection, Wearable device, Mobile phone, Accelerometer, Gyroscope.

1. Introduction

Falling, which means losing one's balance or tripping over something, occurs in all age groups, but especially in the elderly. In Asia, senior citizens over the age of 65 experience over half of the body injuries caused by falling [1-3]. In spite of extensive preventive efforts, falls remain the leading cause of accidental deaths among the elderly. Research estimates that over a third of the people aged over 65 suffer from a fall each year, and the number of falls increases progressively with age in both genders and in all racial and ethnic groups [4]. Because of vision and other problems, the falls typically occur in certain environmental conditions. Falls cause serious damage, including fractures, brain damage, and anxiety toward exercise [5-6]. Quickly dealing with a fall injury such as a broken bone will reduce the time the bone fragment remains in the body. Moreover, some fractured bone regions never completely heal if they do not receive proper care within four hours. If a person falls and bumps his or her head, he or she can black out, and any resulting brain damage should be cared for in a short amount of time to reduce side effects such as paralysis. Reducing the time until treatment can also help prevent a second injury and pain.

The fall detection research was based on epidemiological studies that investigated the experiences of falls by their families [7], evaluated the risk of falls with varying speed using treadmill and the risk of falling, such as walking speed, stride and irregularity of stride [8]. In addition, studies were conducted to measure body movements in everyday life using angular velocity data using high-speed camera, evaluating walking status from acceleration waveforms obtained using an acceleration sensor, and evaluating falls using activity [9]. However, these studies are potentially conscious of the subjects' awareness of the study of falls, and thus have difficulties in measuring in response to various environments where falls occur and are difficult to apply to real life situations. For this reason, the user is not conscious, automatically detects a fall, and you can define detection device is required.

For rapid treatment, the most important challenge is fall detection, which simultaneously provides communication of the fall. Therefore, fall detection is critical. A mobile phone with a three-axis accelerometer and gyroscope is a device that can easily carried by humans. In this paper, a mobile phone is used to classify human falls from normal walking motion. The three-axis accelerometer is used to measure three direction activity data. A gyroscope sensor is used to detect angular momentum; it is also useful in determining the user's rotation when he or she falls. To verify the accuracy of the proposed method, the system and algorithm were validated with a real human data set.

2. Materials and Method

2.1. Data Acquisition

Subjects either walked or fell down while holding a mobile phone in their hand. A three-axis accelerometer was used to detect users' activity such as walking, falling, sitting, etc. When a person falls, one's body rotates on the body's center. A gyroscope that measures angular momentum was used to detect this rotation. The sampling frequency of each data was 20 Hz. The device used for the data acquisition was the Galaxy Note 1 (Samsung Electronics, Seoul, South Korea). The total data set of walking and falling was 212 and 202, respectively. The mean age of the subjects was 23.2; the age range was from 21 to 24.

2.2. Data Analysis

For analysis and synthesis of the plane closed curves, the Fourier descriptor (FD) is used. The normalized Fourier transformed coefficients are called the Fourier descriptors [10]. The discrete Fourier transformation of the signature function is given by the following equation:

$$a_n = \frac{1}{N}\sum_{t=0}^{N-1} r(t)\exp\left(\frac{-j2\pi nt}{N}\right), \quad n = 0,1,\cdots,N-1 \tag{1}$$

The data was produced using a one-point fast Fourier transformation. The FD was extracted from the x-accelerometer, y-accelerometer, z-accelerometer, x-gyroscope, y-gyroscope, and z-gyroscope signals: a total of 96 features were considered. Fig. 1 shows the x-axis accelerometer signal while walking (left) and falling (right) and Fig. 2 presents the x-axis gyroscope signal while walking (left) and falling (right). From the results, we clearly see the difference between the accelerometer signal and the gyroscope signal while walking and falling in the time domain.

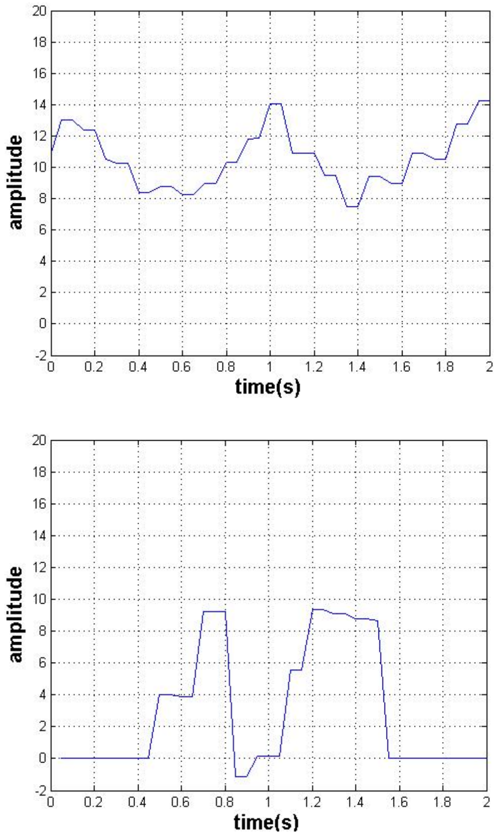

Fig. 1. X-axis accelerometer signal while walking (left) and falling (right).

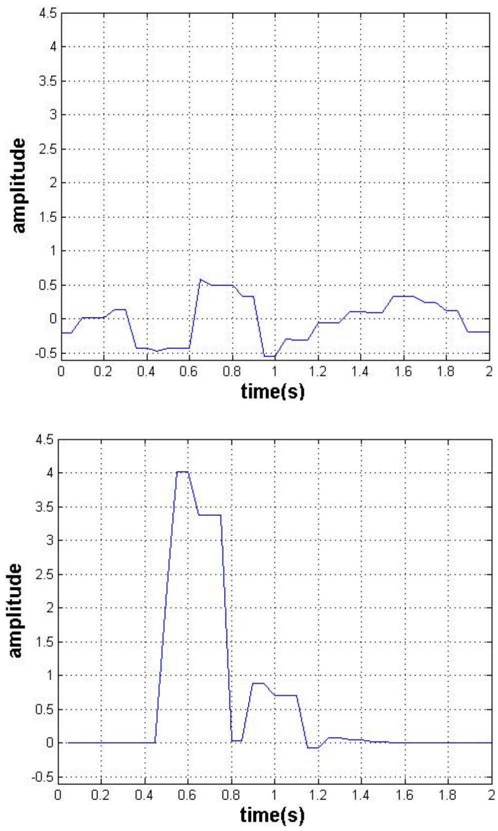

Fig. 2. X-axis gyroscope signal while walking (left) and falling (right).

2.3. Support Vector Machine (SVM) Classifier

The support vector machine (SVM) is a widely used method for classification and regression tasks. For a two-class problem with training samples $\{x_i, y_i\}$,$\mathrm{i} = 1,2,\cdots,\mathrm{N}$ in d-dimensional feature space, $x_i \in R^d$, with associated targets $y_i \in \{-1,1\}$, the discriminate function of the separating hyperplane for linearly separable classes is given as follows:

$$\mathrm{f(x)} = \mathrm{w} \cdot \Phi(\mathrm{x}) + \mathrm{b}, \tag{2}$$

where $\mathrm{w} \in R^d$ is the vector normal to the hyperplane and $\mathrm{b} \in \mathrm{R}$ is the bias. In addition, x_i is the featured vectors extracted from the gyroscope and accelerometer sensors and y_i is the falling and normal status.

The SVM fits a hyperplane to the training samples of two classes in the feature space by minimizing the cost function, which consists of two criteria: margin maximization and error minimization [11]. SVM used real number vector. In this paper, a two-category walk or fall can be showed as (1,0) and (0,1).

2.4. Evaluation Model

The model's accuracy is estimated using a cross-validation method. The data is divided into K to K-fold cross-validation [12]. The subsample left validation data. The other (K-1) data use training data. Validation data is tested using the classifier trained on the remaining training data. In addition, K is repeated, changing the subsample. Each instance of the whole training set is predicted once so the cross-validation accuracy is the percentage of data, which are correctly classified [13]. After that, the results take an average. Y_i is the real response values and X_p is the vector covariates.

$$a_n = \frac{\sum_i (Y_i - a - b_1 X_{1i} - \cdots - b_p X_{pi})^2}{n}, \mathrm{n} = \mathrm{K}, \mathrm{i} = 1,2,\cdots \mathrm{n}, \mathrm{p} = 1,2,\cdots \mathrm{n} \tag{3}$$

TP and TN are the correctly classified occurrences of either walking or falling. On other hand, walking and falling are incorrectly classified as FP and FN. An evaluation was completed using a tenfold cross-validation.

3. Experimental Results

To calculate the classification accuracy, the K-fold cross-validation method was used and K was set as 10. The performance indices were evaluated by five performance indices, including classification accuracy (TP+TN)/(TP+TN+FP+FN), sensitivity (TP/[TP+FN]), specificity (TN/[TN+FP]), positive predictive value (TP/[TP+FP]), and negative predictive value (TN/[TN+FN]), where TP is the number of true positive findings correctly classified as positive; TP = true positive; TN = true negative; FP = false positive; and FN = false negative [14]. As shown in Fig. 3, we noticed that the proposed method detects 384 data (falling or walking) out of 414 original data (falling or walking). The statistical analysis shows that the resulting accuracy was 96.14 %, sensitivity was 100 %, specificity was 92.08 %, positive predictive value was 92.98 %, and negative predictive value was 100 %.

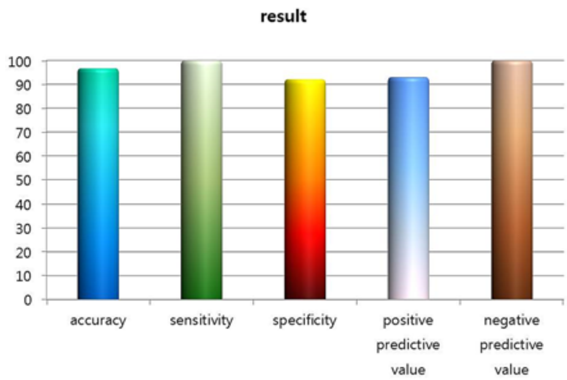

Fig. 3. Statistical analysis results for proposed method verification.

4. Discussion

An elderly person with poor judgment and ability to cope with situations experience frequent falls due to decreased physical strength and sense of balance. Of the elderly people aged 60 or older, 25 % to 30 % experienced falls, 35 % of those over 70 years, and 50 % of those over 80 years of age [15]. Some elderly people experience a fall, and their lifestyle changes dramatically, leading to a syndrome in which physical mobility declines due to fear of falls [16]. Falling occurs in all age groups, but clinical problems due to falls are more associated with physical conditions such as osteoporosis and reduced protective reflexes. In particular, fracture can easily occur due to a decrease in bone density. Elderly people with chronic diseases are injured by unexpected falls, and these injuries lead to impairment of body function and complicating disease. Falling may cause injury to people, fracture, and tissue damage, so quick emergency care is needed.

In this paper, we assumed that the elderly person always carries the proposed platform due to the fact that the ordinal mobile phone motion sensors are what detect the falling status. The current platform can be interrupted with events such as an incoming call, or if the motion sensors are occupied with other applications, the motion-detecting algorithm might be hold. Further, we assumed that the small and portable sensor attached to the elderly person will be carried by the same elderly person. Finally, the deliberate fall of young people is quite different from the fall of elderly people, and their walking patterns might also be quite different. In future work, the clinical trials of real data sets from both old and young people will be obtained and analyzed to optimize the fall detection algorithm for ordinary people.

u-healthcare extends the scope of the healthcare market, including silver towns, a paradigm of disease management and prevention [17]. Especially in the case of the elderly, prevention of falls and emergencies is expected not only to save a lot of medical expenses resulting from u-healthcare, but also to significantly improve the life. In addition to the silver care service for the elderly, the market for healthcare services for the general public is increasingly in need of technologies based on bio-signals [18-19]. Silverware-based elderly fall detection is a very necessary technology in terms of demand, need and technical value.

5. Conclusion

In this paper, we propose a mobile phone-based falling detection sensor and algorithm. We used a three-axis accelerator and three-axis gyroscope to determine the direction and rotation of the subjects' bodies. The support vector machine classifier was used to analyze the sensor's signal. From the experimental results, the proposed method detects falling status with 96.14 % accuracy, which indicates that human activity can be classified using a mobile phone. These detection methods can warn others of a user's fall.

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