Wearable Wireless Fall Detector for the Elderly

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Abstract

In this work, a wearable wireless automated fall detection system is developed that consists of six body-worn inertial and magnetic sensors mounted on subject's head, chest, waist, right wrist, right thigh and right ankle. Each sensor unit measures acceleration, rate of turn and the strength of the Earth's magnetic field along three perpendicular axes (x, y and z). Six volunteers performed a set of movements including falls and activities of daily living (ADL). Falls are distinguished from ADL tasks using dynamic time warping (DTW), least mean square (LMS), k-nearest neighbor (k-NN) and artificial neural network (ANN) classifiers. The best classification rate is achieved by the k-NN algorithm with 99.01% specificity, 100% sensitivity and 99.44% accuracy.

***Keywords**:* Biomechanics, fall detection, inertial sensors, classification, body area networks.

1. Introduction

Falls can be defined as involuntary events resulting in a person coming to rest on the ground [1]. Falls are a public health problem and a health threat, especially to adults of age 65 and older. Statistics show that one in every three adults experiences at least one fall every year. Intrinsic factors associated with falls are aging, neurologic and orthopedic diseases, vision and balance disorders. Extrinsic factors are multiple drug usage, slippery floors, poor lighting, loose carpets, handrails near bathtubs and toilets, electric or power cords, clutter on stairways and obstacle. Most falls occur at home; therefore, they can be prevented by eliminating environmental risk factors at home. However, intrinsic factors such as age, gender or mental impairment may not be changed. Although a physician can help improve some health conditions, there is no guarantee that falls can be prevented.

Fall related serious injuries such as hip fractures and head traumas or other complications are the leading causes of early death. 67% of adults age 85 or older is admitted to a hospital for fall related injuries. The highest fall death rate in older adults belongs to adults with age 85 or older because the hazards of fall related injuries increase as age increases. The number of hospitalizations due to fall related injuries rises each year because of increased population of elderly people in the world. As a result, the cost of health care is increasing every year. In the United States alone, the total charge for older adults hospitalized for fall related complications were 20 billion dollars in 2011 and it is expected to be 48 billion dollars in 2020. Falls are not only a threat to elderly people but also to individuals living with some neurologic or orthopedic diseases. Some diseases such as osteoporosis can make the bones of elderly people more fragile and more prone to falls than young people. Since falls among older adults are a serious and costly health problem, they should be detected to reduce fall related injuries. There are two types of fall detection: user activated and automated systems. However, a fall detection system must be automated because falls may cause loss of consciousness or vice versa.

Falls can be detected by using various automated methods such as camera systems, smart floors and sensors. Each of these systems has its own advantages and disadvantages. Automated fall detection systems can be divided into two categories: active and passive sensing [2]. In active sensing, falls are detected by sensors attached to the subject's body. These sensors are usually accelerometers, and falls are detected by thresholding the total acceleration. For passive sensing, smart floors or camera systems detect falls by monitoring floor vibrations or images. However, passive sensing has some major disadvantages. Smart floors and camera systems need a studio environment; the person who is being monitored has to live in this restricted area. The installation cost of smart floor system is higher than other systems. Although camera systems are cost-effective, privacy is of concern. Moreover, continuous monitoring may cause stress on the subject, and may subsequently cause changes in the subject's original movements. Furthermore, passive sensing systems force subjects to live in a restricted area, and therefore reduce the quality of life of the subjects.

Active sensing systems do not need a studio environment and can also operate both indoors and outdoors. Recent advances in Micro Electro Mechanical Sensors (MEMS) have significantly reduced the weight, size and cost of inertial sensors as well as made active sensing method using MEMS sensors easy to implement and cost-effective. MEMS sensors, especially accelerometers have been widely used in various studies [3-7] because they offer great sensitivity and specificity. However, since there is no common set of experimental trials, comparing the results among various studies is very difficult.

An ideal fall detection system should be able to distinguish falls from ADLs with 100% specificity and 100% sensitivity. Although some studies were able to produce these incredible results in laboratories, these systems produce poor results with real-life users, who are not involved in the tests. To reduce performance loss and enable result comparison among various studies, a standard set of fall and ADLs tests is necessary [8].

Recently, a set of movements including falls and ADLs was proposed by Abbate et al. [9]. In this work, these movements were performed by six young volunteers and were recorded with six wireless body-worn inertial and magnetic sensors (Fig. 1). There were 20 falls and 16 ADL events and each test was repeated five times by each volunteer. Falls were distinguished from ADLs using different classifiers: dynamic time warping (DTW), least mean square (LMS), k-nearest neighbor (k-NN) and artificial neural networks (ANN) methods. The best classification rate was achieved with the k-NN algorithm with 99.44% accuracy. The same work provides some guidelines in fall detection experiments and construction of the database. We tried to incorporate most of the suggestions in [8, 9] in this study.

This paper is organized as follows. The details of the experiments are given in Section 2. Feature extraction, classification process and signal processing algorithms are described in Section 3. Results and conclusions are given in Section 4.

2. Experiments

With Erciyes University Ethics Committee approval, Fall and ADL tasks were performed by six young healthy volunteers (three males and three females) at Erciyes University Clinical Research and Technology Centre. Males are 21, 23 and 27 years old with body masses of 81, 78 and 67 kg and heights of 174, 180 and 176 cm, respectively. Females are 21, 21 and 19 years old with body masses of 51, 47 and 47 kg and heights of 170, 157 and 166 cm, respectively. Table. 1 and Table. 2 show the simulated falls and ADL as performed by the subjects. There are 36 tests total, and each test was repeated 5 times by each volunteer, resulting in a total of 1,080 records (36 tasks x 5 repetitions x 6 volunteers).

2.1. Materials

Tests were recorded wirelessly with a remote PC over RF. Volunteers were given six wireless miniature inertial and magnetic sensors. Sensors were mounted on subject's head, chest, waist, right wrist, right thigh and right ankle with special strap sets as shown in Fig. 2. Sensors used in this project are a part of the MTw development kit and produced by Xsens Technologies [10]. This kit includes six MTw sensor units. Each unit has one tri-axial accelerometer, one tri-axial gyroscope and one tri-axial magnetometer with the respective range of ±120 m/s^2, ±1,200 deg/s and ±1.5 Gauss and one atmospheric pressure meter with the range of 300-1100 hPa. However, pressure data were not used in classification. These sensors sent measurement data over RF to a radio station unit called Awinda Station. This unit was connected to a remote PC with USB interface and sensors were monitored/recorded in real time.

A record contains acceleration, rate of turn and the strength of the Earth's magnetic field along three perpendicular axes (x, y and z). A sampling frequency of 25 Hz was defined. Sensors were calibrated before each volunteer started the experiments. Sensors were programmed with MT Manager Software coming with MTw Development Kit. Raw data were captured and recorded with the same program interface.

MT Manager Software guarantees capturing all data which are generated by the sensors up to 32 MTw units. MTw units can detect packages which are lost during the transmission when facing transient data loss in the RF transmission immediately retransmit the lost packages to the Awinda Station.

Fig. 1 MTw unit (reprinted from http://www.xsens.com/en/mtw)

All sensor units were mounted on a subject's body tightly with special apparatus. These straps set help to obtain realistic body movements and prevent sensors from unwanted shocks or accelerations. In the literature, sensors are generally attached to a subject's body with a tape or rubber. However, such apparatus cannot connect sensors tightly and may be loosened during the experiments. Wireless data transmission is another advantage of our system because cables can disturb a subject when s/he performs the experiments, while wireless sensors allow a subject to move freely. Therefore, natural movements were more likely to be obtained from our experiments.

Fig. 2 Sensor replacement on a subject's body.

2.2. Tests

A set of experiments including falls and ADLs were performed by six young healthy volunteers. Experiments contain 20 falls and 16 ADLs as shown in Table. 1 and Table. 2.

Table. 1 Simulated falls [9]

	Description
1	From vertical going forward to the floor
2	From vertical going forward to the floor with arm protection
3	From vertical going down on the knees
4	From vertical going down on the knees and then lying on the floor
5	From vertical going down on the floor, ending in right lateral position
6	From vertical going down on the floor, ending in left lateral position
7	From vertical going on the floor and quick recovery
8	From vertical going on the floor and slow recovery
9	From vertical going on the floor, ending sitting
10	From vertical going on the floor, ending lying
11	From vertical going on the floor, ending lying in right lateral position
12	From vertical going on the floor, ending lying in left lateral position
13	From vertical going on the floor, ending lying
14	From vertical going on the floor with subsequent recovery
15	From vertical going on the floor, ending lying
16	From vertical going on the floor with subsequent recovery
17	From standing going on the floor following a vertical trajectory
18	From standing going down slowly slipping on a wall
19	From vertical standing on a podium going on the floor
20	From lying, rolling out of bed and going on the floor

Fall experiments were performed by six volunteers and each task was repeated five times. A total of 600 records (20 tests x 6 volunteers x 5 repetitions) were achieved from the fall tests. Soft crash mats were used in both simulated falls and ADL to prevent the subjects from injuries. Moreover, the volunteers were asked to wear a helmet, knee pads, elbow pads and wrist guards for extra safety precautions.

Table. 2 ADL actions [9]

	Description
21	From vertical lying on the bed
22	From lying to sitting
23	From vertical sitting with a certain acceleration on a bed (soft surface)
24	From vertical sitting with a certain acceleration on a chair (hard surface)
25	From vertical sitting with a certain acceleration on a sofa (soft surface)
26	From vertical sitting in the air exploiting the muscles of legs
27	Walking forward
28	Running
29	Walking backward
30	Bending of about 90º
31	Bending to pick up an object on the floor
32	Stumbling with recovery
33	Walking with a limp
34	Going down, then up
35	Bending while walking and than continue walking
36	Coughing or sneezing

ADL were also performed by six volunteers, and each test was repeated five times, resulting in the total of 480 records (16 ADLs x 6 volunteers x 5 repetitions).

3. Signal processing

A raw dataset of 1,080 actions, 600 falls and 480 ADLs was created after the experiments. Each record lasts about 15s on the average and consists of accelerations, rates of turn and the Earth's magnetic field along the three axes (nine values in total). The experiments were recorded by a PC using MT Manager software; therefore, the records were in a special file format. These files were extracted and converted to ASCII text format with the same software, resulting in six different files. Each file represents an individual sensor at the head, chest, waist, right wrist, right thigh and right ankle.

3.1 Feature extraction

In this work, the sensor mounted on the waist of a subject was selected as a reference vector because the waist is the closest point to the body's center of gravity. Moreover, the waist will move only if the trunk moves. However, the head or the other outer parts of the body such as the arms can move even if the trunk is stationary. The maximum activity region is defined with the total acceleration vector (TAV) in the waist sensor (Eq. (1)). Here, A_x, A_y and A_z are the acceleration ratio measured along the three axes.

$$TAV = \sqrt{A_x^2 + A_y^2 + A_z^2} \qquad (1)$$

Maximum total acceleration index was searched in the waist record, and this index was defined in terms of time. Then, the two second intervals before and after this point were saved. Other parts of the record were deleted. These new records consist of 101 samples (25Hz x 2s + TAV index + 25Hz x 2s). The other five sensor's records were downsampled by using the same time index. The new dataset contains six 101 samples of long sensor data for each test. Accelerations, rates of turn and the Earth's magnetic fields along 3-axes result in 101 rows and 9 columns of data. Each column of data can be given as $n \times 1$ vector ($D = [d_1, d_2, ..., d_n]^T$). We applied a set of feature extraction techniques to these data. These features are the minimum and the maximum values, the mean value, variance, skewness, kurtosis, autocorrelation sequence (the first 5 sequences) and the peaks of the discrete Fourier transform (DFT) of the data with corresponding frequencies (the first 5 values with corresponding frequencies) [11].

Feature extraction process was applied to all 1,080 records. Produced features were collected in the following order: first, an arrangement was made for individual sensor units. For a single sensor unit, the first five features are the minimum, maximum, mean, skewness and kurtosis values. This process was applied for each sensor in three axes, and 45 features (9 axes x 5 values) were created after this process. Autocorrelation produced 45 features (9 axes x 5 features). DFT produced 5 frequencies and 5 amplitudes values, resulting in a total of 90 features (9 axes x 10 values). Therefore, each sensor is defined by 180 features (45 + 45 + 90). Each test includes 6 sensors and it is defined by 1,080 features (180 features x 6 sensors). A feature vector, which defines a test, was created by feature vectors of 6 sensors. Feature vectors of sensors were collected to create feature vectors of individual performing tests at the head, chest, waist, right wrist, right thigh and right ankle.

3.2 Classification

Our final data contain a large number of features because each test contains 1,080 features and there is a total of 1,080 records. This large number of features can increase the computational complexity and the difficulty of training and testing the classifiers. As a result, feature dataset was reduced using principal component analysis (PCA) method [12]. The content of each feature vector was reduced from 1,080 to 30, and the final dataset was normalized between 0 and 1.

600 fall events were distinguished from 480 ADL events using four different classifiers: DTW, LMS, k-NN and ANN. The performances of each classifier are given in the following section.

4. Results

The final dataset (30 samples x 1,080 tasks) was divided into two subsamples; 20% was used for training and 80% was used for testing the classifiers. A comparison of the algorithms´ performance is given in Table. 3. TP is True Positive, TN is True Negative, FP is False Positive, FN is False Negative, Sp is Specificity, Se is Sensitivity and Acc is Accuracy. All of the classifiers distinguish falls from ADLs with more than 95% accuracy. However, k-NN classifier is the best performer with 99.44% accuracy, 99.01% specificity and 100% sensitivity.

k-NN algorithm searches the training objects that are the most closely related to the given objects. Class decision is given by maximum neighborhoods. There is no predefined k value because this algorithm is sensitive to local data. Obtained by trial and error, k = 7 was used in this work. Usually, small k increases the variance, while large k decreases sensitivity. Therefore, proper k values strongly depend on the local dataset [13]. LMS and DTW also achieve good performances, and there is no false alarm in the LMS results, similar to the k-NN results.

In the LMS algorithm, signals are compared with the predefined two average reference vectors which are average ADL reference vector and average fall reference vector, and minimum sum square error is searched [11]. Accuracy of LMS is 98.98% with 11 false alarms and 98.2% specificity. LMS also did not miss any fall event and 600 fall events are distinguished from ADLs with 100% sensitivity.

DTW algorithm searches optimal alignment between two given time dependent sequences. It can match the similar waveform even if there is a phase shift in the time axis [14]. Accuracy of DTW is 97.96% and its sensitivity is 99.78%, and its specificity is 96.61%. There are 21 false alarms and one missed fall event in the results of DTW. The number of the false alarms may be ignored but system has to detect any single fall events.

ANN is one of the most preferred classifiers in the pattern recognition area [12]. In this work we used a multi-layer perceptron ANN model which has four layers which are one input layer with 30 neurons, two hidden layers and one output layer has one output neuron. We used Levenberg Marquart (LM) algorithm for training. The results of ANN are not as good as k-NN, LMS and ANNs. 11 falls are missed and 26 false alarm exist. However accuracy of ANN is still more than 95%.

5. Acknowledgement

This work was supported by Erciyes University Scientific Research Project Department under grant number FBA-11-3579 and the Scientific and Technological Research Council of Turkey (TÜBİTAK) 2218 National Postdoctoral Research Scholarship Program.

The authors wish to thank Prof. Kenan Danışman, Director of Clinical Research and Technology Center at Erciyes University, for providing an experimental area during the course of the project.

The authors would like to thank the six volunteers who participated in our experiments for their efforts and time.

Table. 3 Classification performance of the algorithms in terms of specificity, sensitivity and accuracy

	DTW		***LMS***		***k-NN***		***ANN***	
	Conditional Positive	Conditional Negative	Conditional Positive	Conditional Negative	Conditional Positive	Conditional Negative	Conditional Positive	Conditional Negative
Test Outcome Positive	*TP* **599**	*FP* **1**	*TP* **600**	*FP* **0**	*TP* **600**	*FP* **0**	*TP* **588**	*FP* **12**
Test Outcome Negative	*FN* **21**	*TN* **459**	*FN* **11**	*TN* **469**	*FN* **6**	*TN* **474**	*FN* **26**	*TN* **454**
Sp %	**96.61**		**98.2**		**99.01**		**95.77**	
Se %	**99.78**		**100**		**100**		**97.43**	
Acc %	**97.96**		**98.98**		**99.44**		**96.48**	

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