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Fall Detection Using Adaptive Neuro-Fuzzy Inference System

Minoo Rashidpour[1], Fardin Abdali Mohammadi[2,*] and Abdolhossein Fathi[3]

[1]Masters Student, Department of Computer Engineering, Boroujerd Branch, Islamic Azad University, Borujerd, Iran

[2,3]Department of Computer Engineering and Information Technology, Faculty of Engineering, Razi University, Kermanshah, Iran

[1]mrashidpur@gmail.com, [2]fardin.abdali@razi.ac.ir, [3]a.fathi@razi.ac.ir

Abstract

A factor seriously endangers the people health is falling, particularly for patients and the elderly. Fall detection systems contribute in preventing the consequences of the late medical aid and injuries endangering the people health. The main problem within fall detection systems is how to correctly distinguish between a fall and the other daily activities. There are various types of fall detection systems each of which has different advantages and disadvantages. Wireless motion-sensor based systems such as accelerometer and gyroscope provide higher efficiency with lower limits. This study introduces a new fall detection method employing motion sensors in smart phones to collect data due to the ease of access and application. To provide high efficiency for people with various ages and conditions, this method also takes advantages of adaptive-fuzzy neural networks for learning and inference. These methods correctly detect all 4 types of fall from 9 main daily activity groups.

***Keywords**: Fall Detection; Adaptive Neuro-Fuzzy; Inference System; Inertia Motion Unit*

1. Introduction

Today, the population aged over 65 years is increasingly growing in different communities. By 2050, the population of people aged over 65 years will increase by 33% [1]. Therefore, measures should be taken to protect the health of the aged population. A factor that may endanger the health of older people is falling. Fall detection systems can greatly contribute preventing the risks of late medical aids to people injured by falls. In addition to the elderly, patients, athletes who exercise alone and people who live alone are also exposed to the risks of falling. Therefore, fall detection systems help in people health. They also contribute in development of independent life style [2]. In addition, treating injuries caused by falling needs a large amounts of money. For example, in 2000, about 179 million dollars were spent on direct medical expenditure for injuries caused by falls and led to death, and about 9 billion dollars on medical injuries not leading to death [3]. Fall detection methods can significantly reduce such costs. Automatic fall detection can speed up medical aids thus preventing further injuries caused by the inactivity after a fall [4].

The main issue in fall detection is how to distinguish between a fall and other daily activities. Some activities are very similar to a fall, including quick sit, jump, bend, or any fast downward movement [5]. A highly efficient system should be able to correctly distinguish between such movements and falls. With technological advancement in medical equipment, wearable wireless sensors are highly considered due to the small size and ease of use. Wireless sensors are not limited to a particular location, while image processing and camera-based systems are limited to the location where the camera is mounted. Another important specification for fall detection systems is to correctly detect

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falls for people with different spatial and motion features. Thus, to clearly detect the fall we need to clearly define it.

The rest of this paper is organized as follows. Section 2 reviews various fall detection methods ever introduced. Section 3 presents a new fall detection method based on ANFIS. In Section 4, the proposed method is presented and implemented in Matlab. In Section 5, the proposed method that in Section 4 was presented is evaluated. Finally, future work and conclusions obtained from this study are provided in Section 6 and 7, respectively.

2. Related Work

According to the classification provided in [6], fall detection methods are categorized into three categories:

(1) Methods based on sensors wearable or mountable on the body that will be discussed in detail. Such sensors include accelerometer, gyroscope, *etc.* Each type is available in various types and the tri-axial sensors are the most useful and efficient ones.
(2) The image-based methods, such as [7-10] which all contains a camera. For such methods, fall is detected through image processing.
(3) Methods based on environmental sensors which employs various sensor signals, such as sound, video, or the vibration sensors, to detect a fall. For example, in [11] and [12], sound and video signals are used for fall detection, respectively. In addition, a system based on floor vibration is introduced in [13] for fall detection.

Figure 1 shows the categories and types of fall detection methods.

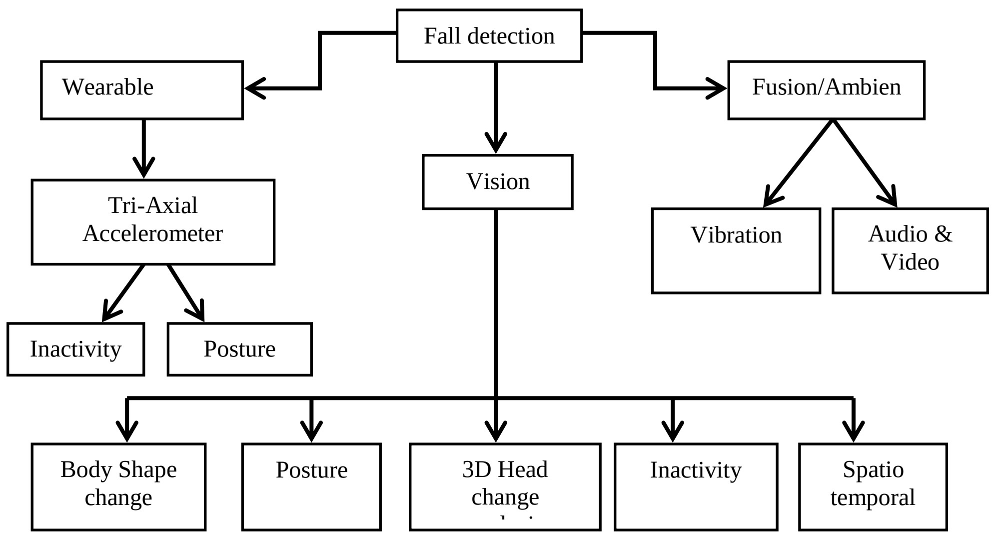

Figure 1. Classification of Fall Detection Methods in [6]

Among the wide range of previous studies conducted on fall detection, recognizing the acceleration of the body is a crucial part for correct analysis. Methods included in the second and third categories contain spatial restrictions. This means that they are effective only in the place where cameras or environmental sensors are mounted. While, methods based on wireless sensors, such as accelerometer and gyroscope, do not comprise such spatial restrictions. Thus, people choosing such systems can simply use them anywhere. Some systems are developed only based on the methods calculating the acceleration of the body, which can increase accuracy and reduce false alarms. As a result, systems not employing the acceleration are less accurate with many false alarms. A series of experimental studies were conducted on fall detection methods employing the acceleration at the University of Nebraska at Omaha in the US. Findings demonstrate that the MEMS accelerometer is able to detect a fall with the sensitivity (the ability of the algorithm in correctly detect a fall) of 80% and the specificity (the ability of the algorithm in correctly detect a no-fall) of 88%. Additional motion sensors, such as the gyroscope, can help categorizing events as a fall or a routine activity more accurately, thus increasing the accuracy [14]. Therefore, this study focuses on methods based on sensors mountable on the body and employs it in the proposed method.

Methods based on wearable sensors usually use accelerometer and gyroscope sensors to calculate acceleration and angular velocity. These sensors are mounted in different parts of the body (head, chest, the thighs, and reins) in different methods. According to the study by Kangas *et al.* [15] on comparing various algorithms, methods in which sensors are mounted on reins or head provide better result with smaller errors.

Bourke *et al.* in a study on fall detection employed two 3D accelerometer: one mounted on the chest and the other on the thigh. According to this study, if the accelerations calculated from the sensor on the chest and thigh are out of 0.41-3.52 and 0.6-2.74 ranges, respectively, then a fall is detected [16].

To detect a fall, Li *et al.* employed two sensors (a tri-axial accelerometer and a tri-axial gyroscope) one mounted on the tights and the other on the chest. In this way, if the body position before lying down is not intentional, it is considered as a fall. An intentional or unintentional position is determined through the linear acceleration and angular velocity. The process includes three steps: 1) motion intensity analysis; 2) body position analysis; and 3) transition analysis. If the both linear acceleration on the chest and tights and the rotation rate are less than 0.4g and 60 °/s, it is recognized as a static position, otherwise as a dynamic position. For the static position, accelerations are read to determine the specific conditions (such as standing, bending, sitting and lying down). For static lying-down position, it is examined if the transition to lying-down position was intentional or unintentional. For this, the data for 5-last seconds is used. If it is recognized as an unintentional transition, it is considered as a fall [17].

To detect a fall, Bourke & Lyons just employed a bi-axial gyroscope. In this study, the algorithm considers three thresholds to define a fall. When the resultant angular acceleration, angular velocity, and changes in the angle of the upper body are more than 0.05 rads/s2, 0.1 rads/s, and 0.59 rad, respectively, it is considered as a fall. This approach first measures the resultant angular velocity, if it does not exceed the defined threshold, the motion is not considered as a fall. Otherwise, the resultant angular acceleration (derivation of angular velocity) and the resultant changes in the angle of the upper body (integral of angular velocity) are measured. If the specified thresholds are exceeded, a fall is detected [18].

Huynh *et al.* employed an accelerometer and a gyroscope in the system proposed for fall detection. To define the fall, they considered the lower and upper threshold. When the acceleration vector is less than the lower threshold, and the angular acceleration and the acceleration for 0.5 seconds after the motion are higher than the upper threshold, then a fall is detected by the system [19].

Peter Mostarac *et al.* used a tri-axial accelerometer to detect a fall. To define the fall, they considered the definition of impact. If a single-impact is recognized while the body has no change in orientation, a fall will be detected. To detect the impact, the acceleration and the body orientation are investigated. The algorithm first examines the impact to body. If an impact is detected, it will be checked whether there was any impact in determined intervals before and after the target impact. In case there is no impact, the body orientation in 1 second before the first impact and 2 seconds after the last one are calculated for two sensors. If the changes in body orientation are more than the defined threshold (in each sensor), then a fall is detected [20].

Bourke *et al*. examined fall detection algorithms based on 3D accelerometer attached to the back during continuous script and non-script activities. To define a fall, the method tested in this study considers three thresholds for velocity, intensity of impact, and body position. The value displayed by the tri-axial accelerometer mounted on the back is saved and compared by the defined thresholds. According to the algorithm, if a threshold is exceeded, a fall is happened [21].

Lina Tong *et al*. also introduced a method for fall detection as well as prediction employing 3D accelerometer based on hidden Markov model (HMM). Here, there are two thresholds: one for fall prediction (0.334) and one for fall detection (12.3). If the thresholds are exceeded, a fall is predicted or detected. This method uses HMM to define thresholds and uses the accelerometer to measure the body acceleration [22].

To detect a fall, Tong Zhang *et al*. employed a wearable sensor and NMF algorithm. Here, fall is defined as an unintentional motion having three steps: daily activities, fall followed by a period of inactivity. This method first measures the total acceleration which is sum of the three accelerations in three axes. If the total acceleration is close to |g|, an inactivity is recognized. Thus the data for 1.5 seconds before the inactivity as well as the severity of changes in vertical acceleration are investigated [23].

Michal Kepski *et al*. in [24] employed the fuzzy inference for fall detection based on a system composed of the accelerometer and Kinect. Here, fall is detected through a fuzzy inference engine based on the expert knowledge specified by the rules in fuzzy sets. Inputs to the system are acceleration, angular velocity and center of gravity of the moving person measured by the accelerometer, gyroscope, and Kinect respectively. If a certain number of samples exceeded the pre-defined threshold over a period, then a fall is detected.

In [25], Chia Chi Wang used triaxial accelerometer in fall detection. To define a fall, he considered total acceleration both in the three axes (called Sa) and horizontal plane (called Sh) as well as the maximum velocity. In a normal movement, Sa is higher than 6g and Sh remains under 2g. When the acceleration exceeds the threshold, a fall is detected. Here, a velocity more than 2 m/s is defined as the threshold.

Chen *et al*. [26] employed a triaxial gyroscope attached to the back to detect a fall. To distinguish between a normal movement and a fall, the algorithm examines three factors: magnitude of acceleration vector, velocity on the horizontal plane, and velocity on the reference plane. If the body acceleration is greater than the pre-defined value with the direction of either forward or backward, and after the movement the body is at rest, a fall is detected.

In [27], Endo *et al*. considered a framework for normal motion to detect a fall. This study also employed two thresholds: one determining whether the data is within the framework, the other determining whether the data is a value between the maximum and minimum. If no, a fall is recognized.

To detect a fall, Enomoto in [28] employed a sensor attached on the right thigh. Here, a fall is detected through three steps: acceleration analysis; angular velocity analysis; and angular changes analysis. The analyses are based on the threshold values. If a fall is detected by the three analyses, then the fall alarm is activated.

To detect a fall, [29] uses the machine learning, especially the decision tree. Acceleration and angular velocity are obtained through triaxial accelerometer and gyroscope. Then data is transferred to a PC via Bluetooth for further processing.

In [30], two steps are considered to detect a fall: 1. If the magnitudes of 3D acceleration or the acceleration in x-y plane exceed the corresponding threshold values, it is likely to be a fall. 2. Here, a possible fall is considered as a certain fall if while changing the body angle, no motion is recognized in 4 seconds after the possible fall.

3. Proposed Method

Numerous fall detection methods have already been introduced mainly limited to a particular group of people. This means that such systems are only applicable for people who the system is designed based on their motion features. The advantage of systems designed based on machine learning is that they utilize the motion patterns of each individual for him. Therefore, they are applicable for all people with various spatial, age and motion characteristics.

Most fall detection methods based on wearable wireless sensors consider a threshold value for acceleration, angular acceleration, *etc.* to distinguish between daily activities and falls. There is a problem when considering threshold values. For example, consider two activities with insignificant differences in acceleration or angular acceleration both near the threshold. They two may be either a daily activity or a fall. But it is possible for the algorithm to recognize one activity as a normal motion and the other one as a fall. Employing ANFIS, this study introduces a fall detection method.

The dataset employed in this study was the one provided by George Vavoulas *et al* in [31]. This data set contained signals recorded by gyroscope and accelerometer sensors in smart phones. Named Mobifall, this data set can be downloaded in website for Biomedical Informatics & eHealth Laboratory at the Technological Educational Institute of Crete. The signals of gyroscope and accelerometer sensors record 4 different types of falls and 9 the daily activities. Data collected from the accelerometer and the gyroscope are the acceleration and angular velocity, respectively. A Samsung Galaxy S3 smartphone with static module of LSM330DLC (3D accelerometer and gyroscope) were used to record the data. In addition, a new Android application was employed to record the raw data of acceleration, angular velocity, and direction as sensor-delay-faster parameter with the highest possible sampling rate. The standard deviation of the sampling period was approximately 7.6 ms with an average frequency of 87 Hz for accelerometer and approximately 0.3 ms with the average sampling rate of 200 Hz for both gyroscope and direction data. The application used a SQLite database to save motions. User was allowed to import, edit, or delete activities. An automatic timer was also used to stop the data record at the end of the test. Tables 1 and 2 lists falls and daily activities done by volunteers.

Here, adaptive-neuro fuzzy inference system was used to design an inference system. In this approach, two inference systems were separately designed for acceleration and angular acceleration detecting in parallel a fall or daily activity. Detecting a fall by each of the two systems means a fall.

Table 1. Falls Recorded in Mobifall Data Set

Code	Activity	Time (sec.)	No. of repetition	Description
FOL	Forward-lying	10	3	Fall Forward from standing, use hands to dampen fall
FKL	Front-Knees-Lying	10	3	Fall forward from standing, first impact on knees
SDL	Sideward- Lying	10	3	Fall sideways from standing, bending legs
BSC	Back-sitting-chair	10	3	Fall backward while trying to sit on a chair

Table 2. ADL Recorded in Mobifall Data Set

code	Activity	Number of repetition	Time
STD	Standing	1	**5min**
WAL	Walking normal	1	**5min**
JOG	Jogging	3	**30sec**
JUM	Jumping	3	**30sec**
STU	Stairs up	6	**10sec**
STN	Stairs down	6	**10sec**
SCH	Sit chair	6	**6sec**
CSI	Car step in	6	**6sec**
CSO	Car step out	6	**6sec**

In the inference system based on the human body acceleration, input is the body acceleration gained through triaxial accelerometer. Output is *fall/non-fall* meaning a fall is occurred or not. Acceleration displayed by the 3D accelerometer is three values indicating the acceleration in *x*, *y* and *z* axes. The proposed inference system, to reduce the system complexity and specificity, considered the total acceleration rather than the acceleration in each axis. The total acceleration is calculated according to Eq. 1:

$$a_T = \sqrt{{a_x}^2 + {a_y}^2 + {a_z}^2} \tag{1}$$

Generalized Bell was considered as the input membership function for fuzzy inference system (FIS). Generalized Bell is calculating as Eq. 2.

$$gbell(x; a, b, c) = \frac{1}{1 + \left|\frac{x - c}{b}\right|^{2b}} \tag{2}$$

Where *a*, *b*, and *c* are initial parameters that determined after system train. Output was considered as a constant (0, 0.5, 1). This means that 0, 0.5 and 1 were considered for inactivity and slow motions, daily activities, and fall, respectively. The next step in the design of a FIS was to select rules of inference. As we know, when a person falls, the body acceleration suddenly increases. However, it is not reasonable to consider a constant acceleration as the threshold above which all motions are fall and vice versa. Because this value may differ for people in different situations and ages. This is why we employed a fuzzy system in fall detection. Based on the three membership functions for input and output, three rules were established for this system as follows:

(1) If the body acceleration is low, then the body is nearly inactive.
(2) If the body acceleration is medium, the body is normally active.
(3) If the body acceleration is high, it is a fall.

Employing the rules and the designed membership functions, the FIS was completed thus connecting inputs to corresponding outputs to reach an appropriate output. This means that the system used rules and membership functions to recognize an input acceleration as *fall* or *no-fall*.

However, as discussed, to accurately detect a fall, the system needs the parameters of membership functions to be correctly set. It is crucial how to define the parameters. Since varying for people with different motion parameters, the parameters cannot be entered manually. For this, we employed the adaptive fuzzy neural network to define the parameters. Neuro-adaptive learning is similar to neural networks in terms of functionality. The adaptive learning technique creates a fuzzy modelling process for data to learn from a data set. Via the adaptive learning, parameters of membership functions are defined so that the FIS adapts to the input/output dataset. In the system, membership function parameters were set through a combination of back-propagation and least squares algorithms. This allowed the fuzzy system to learn the structure from the training data set. Here, the training data set varies for each person and is based on the person's motion data. ANFIS was first introduced in 1993 by Zhang [32]. This is a global tool used to estimate the real continuous functions in limited range applicable for any degree of accuracy. Neuro fuzzy is similar to FIS in terms of efficiency. The complex training algorithm employing both gradient descent and least square methods is introduced, it is discussed how to quickly adapt to and train the FIS equivalent to the algorithm.

FIS includes an input x (acceleration) and output z. Sugeno first-order fuzzy model is described by three fuzzy *if-then* rules:

1. If x is A_1, then: $Z = p_1 x + r$ (3)
2. If x is A_2, then: $Z = p_2 x + r$ (4)
3. If x is A_3, then: $Z = p_3 x + r$ (5)

The first layer (input): each node (i) of this layer produces membership values belonging to a suitable fuzzy set using the membership function.

$$O_{1,i} = \mu A_i(x) \qquad \textit{for } i = 1, 2, 3 \tag{6}$$

Where x is the input to i^{th} node; A_i is linguistic tags (such as "low", "medium", or "high") corresponding to the node; $O_{1,i}$ is the fuzzy membership grade for $A = (A1, A2, A3)$ specifying the degree to which x adapt to A; and A is the membership function described by the bell functions. The second layer (membership function input): this layer is composed of a node called Π multiplying input signals then sending it to the output. In other word, here, the operator "and" is used The third layer (the rule): nodes labelled as N calculate the ratio of the i^{th} rule's firing strength to the sum of all rule's firing strengths.

$$O_{3,i} = \overline{w_i} = \frac{w_i}{w_1 + w_2 + w_3} \tag{7}$$

This output is called normalized firing strengths. The fourth layer (membership function output): Every node in this layer is an adaptive node with a node function.

$$O_{4,i} = \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{8}$$

The neuro-fuzzy model allows the fuzzy systems to use adaptive learning algorithm when training parameters. In this method, using the gradient descent algorithm for error, the error is distributed toward the input to correct the parameters. This is identical to error back- propagation method used in neural networks. The total output from the linear combination of parameters can be written as:

$$f = \overline{w_1} f_1 + \overline{w_2} f_2 + \overline{w_3} f_3 \tag{9}$$

$$= (\overline{w_1} x) p_1 + (\overline{w_1}) r_1 + (\overline{w_2} x) p_2 + (\overline{w_2}) r_2 + (\overline{w_3} x) p_3 + (\overline{w_3}) r_3$$

A fuzzy system is implemented so that it can be trained. Thus, the resulting parameters are calculated using minimum mean square error. Combining this method and error back-propagation method, we had a hybrid method working as follows:

In both learning approaches, when moving forward, outputs are calculated to the fourth layer. Then, the resulting parameters are calculated by methods such as minimum mean square error. After calculating the error in a backward-motion, the error is propagated on parameters then they are corrected using gradient descent method.

The same inference system was separately designed for the gyroscope. The output of both systems was investigated. If each of the two systems detected a fall, it meant a fall had occurred. We employed the angular acceleration obtained from the gyroscope for cases where the accelerometer failed to distinguish between a fast motion and a fall (due to either the similarity of a motion and a fall in total acceleration or the failure of the inference system designed for the accelerometer). In such cases, the inference system designed for the gyroscope may correctly detect the fall by angular acceleration. Therefore, it can also increase the system's fault tolerance.

4. Implementation

To implement the method presented in the previous section, the toolbox embedded in MATLAB to implement ANFIS was used. In an input matrix for data training, the last column was considered as output and the others as input by the toolbox. The input data matrices included two columns corresponding to the total acceleration in the x, y and z directions as initial column. The last column with 0 or 1 was the output of the system in which 0 represented fall and 1 represented no-fall.

Thus, a matrix with two columns was the input to ANFIS as the training data. The first column was the total acceleration and the second one was the output including 1 or 0. After the training data, a FIS should be defined. For FIS, membership functions and rules must be specified. Membership functions for input and output were three gbellmf and three constant functions, respectively. Figure 1 shows the graph for input membership functions.

After defining the inference system, the system output needed to be analyzed based on the defined membership functions and rules. If the output was within the interval [0.8712 1.1288], it would be in the third member function and the initial analysis would detect a fall. The fall interval was determined based on the error after system training. The input data was as a vector with 5 seconds duration. Thus, if the output was within the interval specified for a fall in the mentioned time duration, a fall was initially detected. However, as discussed, some daily activities are very similar to a fall. So if we only consider the output as the final decision, we will wrongly detect such activities as a fall. To distinguish between severe activities and a fall, we needed to consider a period after a motion. For a fall, this period would be an inactive one, while it would not be so for daily activities like jumping or running. Therefore, for final decision, we should have checked the data for 5 seconds after the motion. If an inactivity was recognized, falling was approved. To have an inactivity, the output data must be within [-0.1288 0.5]. Figure 3 is a flowchart illustrating the process. Note that this flowchart displays only the main algorithm and functions employed in the algorithm are not included. The functions examine the output of the designed ANFIS. After defining the inference system, it was saved. The structure of the designed ANFIS is shown in Figure 2.

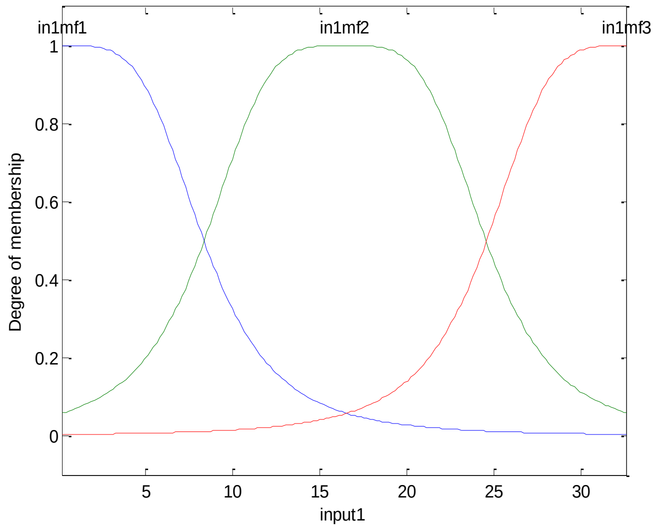

Figure 1. Input Membership Functions

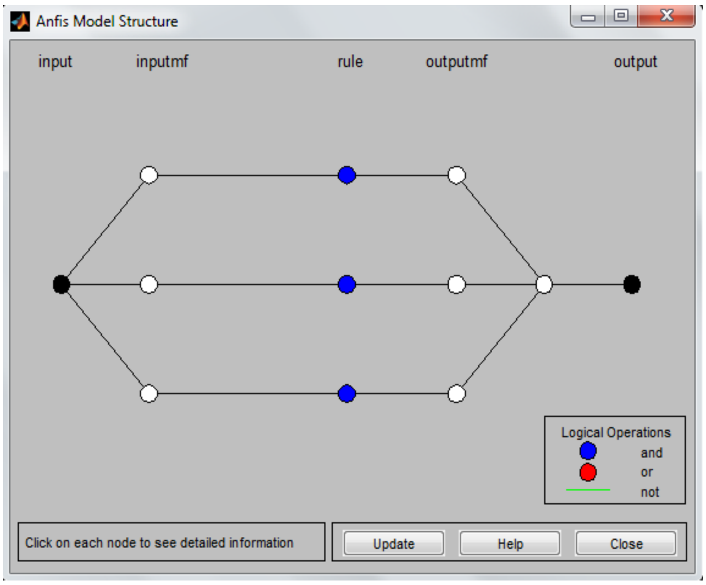

Figure 2. The Structure of the ANFIS Model Designed for the System

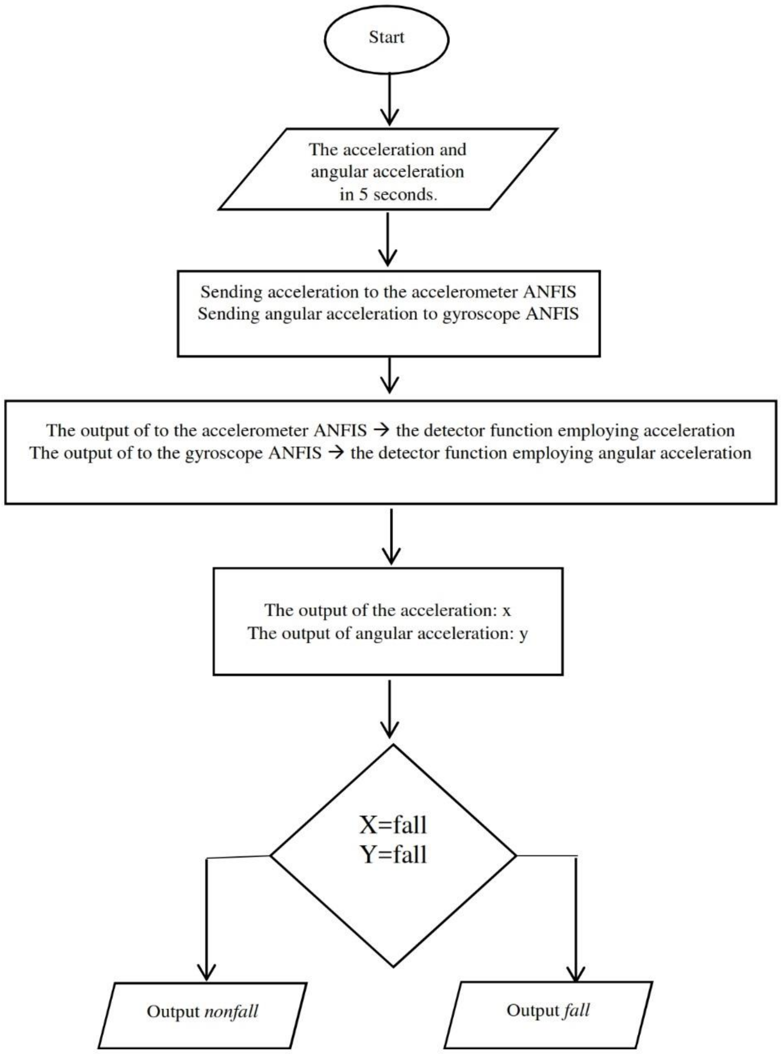

Figure 3. Flowchart for the Proposed Algorithm

Figures 4 and 5 show an example of the system output when distinguishing between a fall and an activity similar to fall. Figure 4 shows the falling backward from the chair and Figure 5 shows a person jogging.

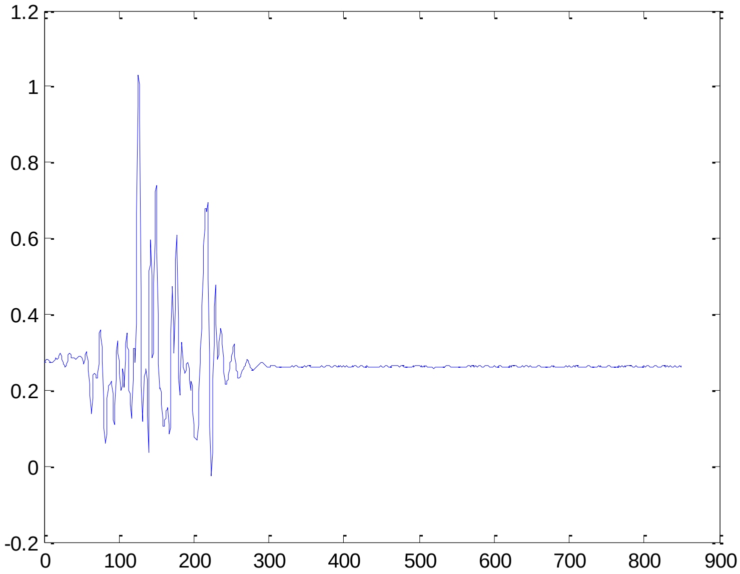

Figure 4. An Example of the System Output when Falling Backward from the Chair

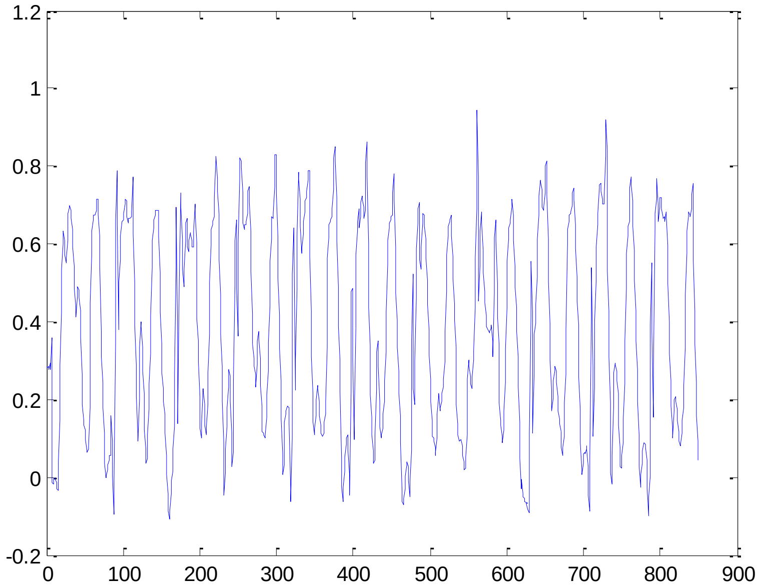

Figure 5. An Example of the System Output when Jogging

As obvious in the figures, for falling backward from the chair, after the fall which happens at the peak of the graph, there is a period of inactivity; that is, about 4 seconds after the peak, the graph is near flat. This is different for jogging and the graph is oscillating.

Some falls may not be detected by the accelerometer. For this, the process was repeated for angular acceleration measured by the gyroscope. If either accelerometer or gyroscope detected a fall, the alarm would be activated. For this step, the total angular acceleration obtained from Eq. 2 was the input. After learning, the error value was calculated as 0.1553. As a result, the output was considered as a constant in interval [1.16 -0.15]. If the output was greater than 0.8 and after the peak there was an inactivity period, a fall was detected.

5. Evaluating of the Proposed Method

As mentioned, the data set employed in this study was the Mobifall provided in [31]. In this dataset, all motions including both falls and daily activities, but walking and standing, are repeated at least three times: one iteration for system training; one as checking data; and the third as evaluation data. For walking and standing, because they are of ongoing activities, the whole data collected from one iteration can be divided into three parts.

Table 2 and 3 list the output of ANFIS for 4 types of falling and 9 daily activities for a volunteer, respectively. The output means the value of the maximum point on output vector. To determine the period of inactivity, from 3 seconds after the peak to the end of the output vector will be checked.

Table 3. Output of ANFIS for 4 Types of Falling

Activity type	Output for accelerometer	Output for angular velocity	Inactivity after 3sec	Final output
BSC	1.031	0.776	Yes	Fall
FKL	0.897	0.930	Yes	Fall
FOL	1.070	0.811	Yes	Fall
SDL	0.923	0.829	Yes	Fall

Table 4. Output of ANFIS for Daily Activities

Activity type	Output for acceleration	Output for angular velocity	Inactivity after 3sec	Final output
CSI	0.6217	0.641	No	Nonfall
CSO	0.5125	0.6350	No	Nonfall
JOG	0.9424	1.097	No	Nonfall
JUM	1.0582	1.097	No	Nonfall
SCH	0.3633	0.3388	No	Nonfall
STD	0.2899	0.1539	No	Nonfall
STN	0.7095	0.5257	No	Nonfall
STU	0.7053	0.5470	No	Nonfall
WAL	0.73	0.8056	No	Nonfall

The test was conducted on a 26-year-old man with a height of 169 cm and weight of 69 kg. As shown in Table 3, falls were better detected by accelerometer than gyroscope. However, employing both accelerometer and gyroscope, we can ensure that if a fall is not detected by the accelerometer, the gyroscope will detect it. And as shown in Table 4, activities such as jogging, walking and jumping are similar to a fall. Such activities are first considered as a fall. However, because there is no inactivity in next seconds, the fall is not confirmed.

So, the system can accurately detect a fall and no-fall for listed activities. It must be noted that all kinds of motions are certainly not considered; therefore, it is not true to say that 100% of the daily activities will accurately be detected by ANFIS. Yet, the system is applicable for all activities since all types of falls are a subset of activities considered here.

To fairly compare the previous fall detection methods with the proposed method, they must be evaluated in identical conditions. This means that we cannot rely on the results obtained by different methods and we need to implement them for the same volunteer. Since each algorithm is designed for a specific group of people, the result will vary for another group of people with different age and motion features. Therefore, it is very difficult and almost impossible to compare the algorithms. Accordingly, Table 5 lists the advantage of the proposed method compared to previous methods.

Table 5. A Comparison between the Previous Fall Detection Methods and the Proposed Method

Methods	Disadvantages	Our solution
Image-based methods [7-10]	Spatial limitations and inefficient for outside	Using wearable wireless sensors
Methods based on environmental sensors [11-13]	Inefficient in areas where sensors are not mounted	Using wearable wireless sensors
Wearable sensor-based method employing a constant threshold value [16-20, 22, 23, 25-29]	Setting a precise threshold will cause errors in distinguishing between a fall and a day activity near the threshold.	Using fuzzy sets to distinguish between the fall and daily activities
Fall detection methods based on data from a limited group of people [10, 16-20, 22, 23, 25-28]	High efficiency for a group of people and no efficiency for other groups	Using machine learning and employing data specific for a person to detect the fall for the same person

To evaluate and compare fall detection methods, both specificity and sensitivity were used. Sensitivity is the ability of the algorithm in correctly detect a fall and the specificity is the ability of the algorithm in correctly detect a no-fall. Table 6 shows the specificity and sensitivity of the algorithms and the last row is the sensitivity and specificity of the proposed method.

As shown in Table 6, the proposed method can accurately distinguish 9 daily activities and 4 types of fall. These tests were conducted on 11 volunteers including 6 men aged 22 to 32 years with height ranging between 169 and 189 cm and weighing between 64 and 102 kg, and 4 women aged 22 to 36 years with height ranging between 160 and 172 cm and weighing between 50 to 90 kg. Nine participants experienced both falls and daily activities and 2 others experienced only falls.

6. Conclusion

This study introduced a new fall detection method based on Adaptive Neuro-Fuzzy Inference System (ANFIS). The previous fall detection algorithms were mainly designed for a specific group of people with specific age, location and motion features. However, methods based on machine learning tackled this problem by employing each person motion data for him. In addition, many algorithms consider a threshold value to detect a fall. They fail to distinguish between a fall and a daily activity which are similar and near the threshold. To solve this problem, the proposed algorithm employed a fuzzy inference system. Using an accelerometer and a gyroscope, the algorithm analyzed the person situation after a fall and successfully detects all 4 types of fall. Falls and daily activities considered in the study are those covering all motions.

Table 6. Comparison between the Previous Fall Detection Methods and the Proposed Method in Specificity and Sensitivity

No.	Ref.	Number of Sensors	Sensor location	Sensor type	Specificity	Sensitivity
1	[16]	2	Trunk and thigh	accelerometer	91.25% for trunk sensor 100% for thigh sensor	83.3% for trunk sensor 67.1% for thigh sensor
2	[17]	2	Trunk and thigh	Accelerometer & gyroscope	91%	92%
3	[18]	1	Trunk	Two axial gyroscope	100%	100%
4	[19]	1	Chest	Combination of Accelerometer & gyroscope	99.382%	100%
5	[22]	1	Upper trunk	Triaxial accelerometer	88.75%	100%
6	[23]	1	Abdomen	Triaxial accelerometer	96.6% for low acceleration ADL 75% for high acceleration ADL	Fall on soft surface: 98.4% Fall on hard surface: 98.6%
7	[24]	1	Upper trunk	Accelerometer & gyroscope & camera kinect	100%	100%
8	[25]	1	Head	Triaxial accelerometer	100%	100%
9	[27]	1	right of waist	Triaxial accelerometer	Not Evaluation	92.7%
10	[28]	1	right of waist	One wearable sensor	100%	100%
11	[29]	2	Chest & right of thigh	Gyroscope & Triaxial accelerometer	Not Evaluation	With 3 volunteer for training data: 72% With 7 volunteer for training data: 81%
12	[30]	1	Waist	Triaxial accelerometer	Not Evaluation	94.79%
Proposed method	-	2	Trouser pocket	Gyroscope & Triaxial accelerometer	100%	100%

7. Future Works

This study introduced a fall detection method in which a fall and daily activities are distinguished for a person based on the motion data obtained from the person. Here, the motion data are obtained from a smart phone, then transferred to a computer. The computer decides whether the motion is a fall or a daily activity and calls rescue centers in case of a fall. The data transfer between the smartphone and the computer system is a waste of time. It also needs two sources of energy one for the mobile phone and the other for the computer. This method will be more useful if applicable on smart phones. Therefore, it is better to design such systems for smart phones to take advantages of contacting rescue centers in emergency cases. For future work, we intend to employ the proposed method to design an application for smart phones detecting falls and immediately contacting rescue centers.

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