FALL DETECTION SYSTEM FOR ELDERLY PEOPLE
A Neural Network Approach

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Abstract: In this work a new approach for a fall detection system is proposed. The device integrates a 3-axis accelerometer and a 3-axis gyroscope to measure linear acceleration and angular velocities, respectively. Information from both sensors is used to characterize movements through selected features extracted from raw data. A classification system based on a Feedforward Backpropagation Neural Network is then trained, based on the extracted features. The performed tests present low false positives and low false negatives rates with good specificity and sensitivity values.

1 INTRODUCTION

Elderly people are generally affected by different problems such as the diminution of muscle strength, decreased balance, vision difficulties and neurodegenerative diseases, among others. Due to these problems, aged people frequently have less mobility and autonomy, as well as increased difficulties to perform normal daily activities, making them a particular group prone to suffer fall events. In average, each year, one in every three adults over 65 years older experiences a fall event and this ratio increases to one in every two adults aging more than 80 years (Hausdorff et al., 2001; Hornbrook et al., 1994). Falls in the elderly can cause physical damage with moderate to severe injuries, such as soft tissue wounds, hip fractures and head traumas, which remarkably deteriorate the health status of elderly people and can even increase the risk of early death (CDC, 2011).

After a fall event, the individual can become unconsciousness or immobilized and unable to raise or ask for help. In both cases, the individual will remain without medical assistance. In fact, it has been reported that half of the elderly population that suffers a long-lie (involuntarily remaining on the floor for an hour or more) after a fall, dies within six months, even if no sever injuries result from the fall (Noury et al., 2008). Thus, it is very important to provide for assistance as soon as possible when a fall event takes place. Having in mind the described context, the development of intelligent systems able to detect a fall event and send an alert would contribute for a higher quality of life and independent living of the elderly people. The main objective of this work is to introduce a fall detection system based on a machine learning paradigm. The proposed scheme presented good specificity and sensibility rates, which makes it possible to be used in a real scenario situation. Additionally, the used strategy introduces a learning and adaption ability not found in other proposed schemes for the same objective.

2 STATE-OF-THE-ART

To the present date, different solutions have been proposed for fall detection of elderly individuals. The simplest approach consists in using an alarm button that, in case of an emergency, should be pressed to send an alert to a relative or a care given institution. Since an automatic fall detection system would resolve this problem, recently several different technologies and approaches have been proposed with this aim.

According to Noury et al. (2008) a fall event can be described as a series of four stages: the pre-fall phase, the critical phase, the post-fall and the recovery phase. During the pre-fall stage, the individual is performing its normal ADL, including some occasional sudden movements, like sitting or

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lying down quickly, which must be distinguished from a fall. The critical phase is a very brief phase (about 200ms) consisting in rapid movements of the body toward the ground, finalized by a strong shock on the floor. In the post-fall stage the person remains inactive, most of the times in the floor, and this stage could last several minutes or hours. In the recovery phase the person gets up by his own means or with the help from another person (Noury et al., 2008). When a fall happens, there is a brief period of "free fall" during which the vertical speed increases linearly with time due to gravitational acceleration (Noury et al., 2008). In this period, an early detection of the critical phase can be achieved. For this purpose, different approaches have been suggested being the most relevant ones the use of video-based monitoring systems coupled to computer vision techniques, the use of accelerometers and gyroscopes (Noury et al., 2008). Fall detection can also be achieved at the end of the critical phase by detecting the impact shock that happens when the body hits the floor or an obstacle (table, bathtub, stair steps, etc.). This can be achieved by using an accelerometer or a shock detector (e.g. piezoelectric sensor).

Most automatic fall detection systems reported on literature consist in wearable sensor-based devices targeting the critical phase of a fall (either its early detection or the detection of its end). Among the different sensor technologies used, inertial sensors, mainly accelerometers and gyroscopes, are the most referred on the literature (Benocci et al., 2010; Bourke et al., 2007a; Laguna et al., 2010) with other types, such as barometric pressure sensors (Bianchi et al., 2010), also being described.

Fall detection systems based on inertial sensors are probably the most effective ones, since they can better describe movement dynamics.

Although it is possible to identify a fall just recurring to one type of inertial sensors (using only accelerometers or only gyroscopes) some authors refer that, to improve the effectiveness of the system (less false positives and false negatives), a combination of inertial sensors is advisable (Nyan et al., 2008).

3 PROPOSED STRATEGY

Although with different implementations, most works generally use one or several threshold values to identify a fall. This methodology presents some drawbacks. An important one is that the threshold values are highly dependent on the test measurement group.

In this work a fall detection device based on an Artificial Intelligence paradigm is proposed. Instead of using threshold values, a neural network was trained with *fall* and *non-fall* data obtained from a 3-axis accelerometer and a 3-axis gyroscope. The main advantage of this implementation is that the system has a learning capability that allows inferring correlations between the input data and the specific movement (*fall* or *non-fall*).

3.1 System Architecture

The proposed device is composed by a 32 bit microcontroller platform and two sensors, namely a 3-axis accelerometer and a 3-axis gyroscope. It is based on the 32 bit ARM Cortex-M3 processor (MBED) running at 96MHz, 512KB of flash memory, 64KB of RAM.

The accelerometer used was the ADXL345. It is a low power 3-axis digital accelerometer with 13-bit resolution able to measure up to ±16 g.

The gyroscope used was the ITG3200. It is a low power digital 3-axis gyroscope with a 16-bit resolution able to measure angular velocities up to ±2000º/s with a sensitivity of 14.375 LSBs per º/sec.

Along with the described sensors the device also includes an emergency button, a buzzer and a *wifi* module. The *wifi* module is used to send the emergency alert to a server. This server is responsible to send a notification/message to a phone number or email account previously defined.

Although wearable devices can be used attached on different body locations, such as the wrist, the neck, the waist, etc., the proposed system is intended to be used at the waist level because when used on this location, the system is positioned near the body's center of gravity, thus providing reliable information on the subject body movements (Kangas et al., 2008). The system is continuously obtaining samples from the accelerometer and gyroscope in 4 seconds windows, corresponding to a sampling rate of 200 Hz. In this period about 800 samples of the acceleration and angular velocity are collected. From the obtained samples ten features are extracted (the features used are described in the next section) and feed to the implemented neural network, which was previously trained to discriminate *fall* situations from *non-fall* situations.

3.2 Feature Extraction

To reduce the input data dimension we choose to compute, from the raw values of linear acceleration and angular velocity, features that can be used to describe the movement dynamics and, consequently, be used to discriminate a *fall* from a *non-fall* situation. There are ten features extracted from the linear acceleration and angular velocity sample data, namely:

$$F_1 = \frac{1}{3N}\sum_{i=1}^{N}\left(\omega_i^x + \omega_i^y + \omega_i^z\right) \quad (1)$$

where N is the number of samples, ω is the acceleration for axes, x, y and z, and i is the sample index.

$$F_2 = \frac{1}{3N}\sum_{i=1}^{N}\left(\theta_i^x + \theta_i^y + \theta_i^z\right) \quad (2)$$

where θ is the angular velocity for each axis.

$$F_3 = \frac{Var(\omega_x) + Var(\omega_y) + Var(\omega_z)}{3} \quad (3)$$

where *Var()* represents the variance.

$$F_4 = \frac{Var(\theta_x) + Var(\theta_y) + Var(\theta_z)}{3} \quad (4)$$

$$F_5 = Max\left(\underset{i}{Max}\left(\omega_i^x - \overline{\omega}^x\right), \underset{i}{Max}\left(\omega_i^y - \overline{\omega}^y\right), \underset{i}{Max}\left(\omega_i^z - \overline{\omega}^z\right)\right) \quad (5)$$

where *Max()* is the maximum operator and $\overline{\omega}$, is the mean value, and i is the sample index.

$$F_6 = Max\left(\underset{i}{Max}\left(\theta_i^x - \overline{\theta}^x\right), \underset{i}{Max}\left(\theta_i^y - \overline{\theta}^y\right), \underset{i}{Max}\left(\theta_i^z - \overline{\theta}^z\right)\right) \quad (6)$$

$$F_7 = \underset{i}{Max}\left(\omega_i^x, \omega_i^y, \omega_i^z\right) \quad (7)$$

$$F_8 = \underset{i}{Max}\left(\theta_i^x, \theta_i^y, \theta_i^z\right) \quad (8)$$

The last two features represent a dynamic range operator. They can be expressed as follows:

$$S_\omega = \left\{\omega \mid \omega > 500\right\} \quad (9)$$

where ω is the acceleration of any axis.

$$F_9 = \frac{\# S_\omega}{N} \quad (10)$$

$$S_\theta = \left\{\theta \mid \theta > 500\right\} \quad (11)$$

where θ is the angular velocity of any axis.

$$F_{10} = \frac{\# S_\theta}{N} \quad (12)$$

3.3 Neural Classifier

The Feedforward Backpropagation (Rumelhart *et al*., 1986) is an artificial neural system that has been widely used in pattern recognition applications. In most of the supervised applications, this neural network, based in the perceptron neuron, presents a good generalization behavior and shows good computational performance. Nevertheless, there are several issues that make this neural system not appropriated for all applications. The backpropagation algorithm used for training feedforward networks is based on the gradient descent. This method allows us to automatically set the weights of the neurons in a way to minimize the error between the target pattern set and the output pattern set. After ending the training stage, the neural network must map the input vector into an output vector with a minor error. In this application, the input vector contains the values from the 10 chosen features and the target/output vector will represent the fall/non-fall classes in a binary way, establishing one logical bit, "0" to the non-fall situation and "1" to the fall situation. The number of examples that were produced to establish the movement patterns set was 631. The first half of this set is formed by patterns concerning the *fall* class and the other half concerns the *non-fall* class. Several patterns were acquired asking to ten volunteers to perform different motion situations.

The neural network was trained using 70% of the movement/pose situations that were acquired concerning several movement scenarios. The remaining situations (30%) were used to test the neural classifier. The training and the test sets were different and randomly obtained from the total set of fall and non-fall patterns. Several runs were performed using different structures for the neural network model. The experiments were prepared using a *3-fold* (cross-validation) x 20 runs. The correct average classification rate over the validation patterns was 96%. The trial performed using the test set showed a generalization performance which indicates that the system could be used in a real scenario.

4 RESULTS

The device was tested in several contexts that included normal ADL and fall simulated situations. Tests were performed for the same kind of cases used for pattern acquisition, presented on Table 2, by four different individuals (different heights and weights). The device was used on the waist. The four volunteers were invited to act as natural as possible in all situations. Fall simulations were performed with the help of a protection mattress so that the volunteers could reproduce a fall without any constrain of injury.

Each individual performed 3 tests for each situation. The obtained results evidence a very good overall performance of the device. For a total of 180 tests only 9 tests were misclassified, which represents a 95% of correctly classified cases. More important, no false negatives were found, meaning that the device is able to detect all the fall events tested. The failed cases can be explained by the acceleration and angular velocities profiles. The sitting down, jumping and to go on all fours movements could have similar profiles to a fall.

Following the proposal of Noury et al. (2008) for the classification and evaluation of fall detection systems, Sensitivity and Specificity criteria were used to assess the performance of the proposed scheme.

$$Sensitivity = \frac{TP}{TP + FN} \tag{13}$$

$$Specificity = \frac{TN}{TN + FP} \tag{14}$$

where TP, FN, TN and FP are the True Positive, False Negative, True Negative and False Positive cases, respectively.

The obtained Sensitivity and Specificity coefficients were 100% and 91.67%, respectively.

5 CONCLUSIONS

In this work a fall detection device based on a neural network was proposed. This approach revealed to be very effective in identifying falls, presenting a Sensitivity coefficient of 100%. It was not so efficient classifying *non-fall* events, presenting some false positives cases.

Considering that not all the tests for the same type of motion were wrongly classified, this can indicate an underfitting training. Increasing the number of training examples could help to improve the classifier performance in this point.

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