A Neural Network Model Based on Co-occurrence Matrix for Fall Prediction

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Abstract. Fall avoidance systems reduce injuries due to unintentional falls, but most of them are fall detections that activate an alarm after the fall occurrence. Since predicting a fall is the most promising approach to avoid a fall injury, this study proposes a method based on new features and multilayer perception that outperforms state-of-the-art approaches. Since accelerometer and gyroscope embedded in a smartphone are recognized to be precise enough to be used in fall avoidance systems, they have been exploited in an experimental analysis in order to compare the proposal with state-of-the-art approaches. The results have shown that the proposed approach improves the accuracy from 83% to 90%.

1 Introduction

Falls are one of the causes of hospitalization that mostly increases health service costs [1]. In particular, since the risk of falling increases progressively with age, the United Nations advises improving health care for elderly people and creating a supportive environment for them. Fall detection systems have been massively studied [2–5], but they only notify user's acquaintance after a fall occurrence. As such, they do not avoid the fall, whereas this is the goal of Fall Prediction Systems (FPSs). FPSs usually follow a common procedure: first, they collect data from sensors, then, the collected data are analyzed to extract an appropriate feature set. Afterwards, a classification algorithm is applied on the feature set. In this study, new features with combination of a multilayer perceptron neural network are proposed and they are compared with different state-of-the-art approaches.

Most of FPSs analyze user's posture or gait variables. Kinematic-based solutions usually exploit sensors to investigate the characteristics of the movement, in particular accelerometer (for measuring acceleration, i.e., the rate of change of the velocity of an object) and gyroscope (it measures angular rate around one or more axes of the space). Real-time kinematic-based FPSs avoid a fall by alerting the user [6–8] or by using an external aid such as a walker or robot [9,10]. This study investigates kinematic-based FPSs, considering in particular data acquired with gyroscope and accelerometer sensors.

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After obtaining signals from accelerometer and gyroscope, appropriate features should be extracted. Since data collected from sensors contain undesired information, filtering techniques eliminate some frequencies from the original signal to attenuate the background noise and to remove the undesired frequencies. After filtering the collected data, appropriate features should be selected. Afterwards, classification algorithm applied on the feature set to recognize the abnormal walking.

The remainder of the paper is organized as follows. The main features selected in the literature are reviewed in Sect. 2. The set of proposed features is described in Sect. 3. Experimental setup, and the results are presented in Sect. 4. Finally, some conclusions are written in Sect. 5.

2 Related Work

The measurements performed for recognizing a fall usually regard the *acceleration* and *tilt* change. The main features extrapolated from these measurements are reviewed in the following.

Acceleration. While a fall occurs, the acceleration of the body movement changes, so this parameter is investigated in FPSs to determine an abnormal walking [11–13]. Features frequently extrapolated from the acceleration are described in the following. In the presented formulas, $A(t)$ indicates the acceleration and $A_x(t)$, $A_y(t)$, $A_z(t)$ refer to the components of the acceleration in the 3 axes. Furthermore, A_{xi}, A_{yi} and A_{zi} are the discrete i-th acceleration samples in the 3 axes.

- Signal Magnitude Area (SMA)
  SMA can be used to classify the activities of the user [11]. It is computed as:
  $$SMA = \frac{1}{T}\left(\int_0^T |A_x(t)|dt + \int_0^T |A_y(t)|dt + \int_0^T |A_z(t)|dt\right) \quad (1)$$
  where T is the monitored interval.
- Signal Magnitude Vector (SMV)
  SMV is adopted to calculate the resultant of the signal:
  $$SMV = \frac{1}{n}\Sigma_{i=1}^{n}\sqrt{A_{xi}^2 + A_{yi}^2 + A_{zi}^2} \quad (2)$$
  SMV specifies the degree of the movement intensity and it can be a metric in FPSs [6,7,11,13].
- Derivative ($A'(t)$)
  The derivative ($A'(t)$) of the acceleration indicates the vibration of the movement and it is evaluated in FPSs [11].

- Hjorth parameters
  Hjorth parameters are statistical measures of the signal in time domain [14]. They use the variance of the signal $var(A(t))$ in their computation: $Hjorth\ activity = var(A(t))$, which indicates the signal power. $Hjorth\ mobility = \sqrt{\frac{var(A'(t))}{var(A(t))}}$, it is an indicator of the smoothness of the signal curve. $Hjorth\ complexity = \frac{mobility(A'(t))}{mobility(A(t))}$, it effectively measures the irregularities in the frequency domain. The Hjorth parameters are utilized to analyze accelerometer and gyroscope signals in FPSs [7].
- Peak and peak-to-peak
  Peak and peak-to-peak are simple and useful measurements of data changing over time. The peak is the maximum value of the signal over the period of time, and the peak-to-peak is the difference between the minimum and the maximum value of the signal over the period of time. The acceleration amplitude and derivative of peak-to-peak are two features used to predict a fall [15].
- Energy
  The energy of the acceleration signal specifies the amount of activity in the vertical and horizontal directions. It can determine the strength of the contact with the floor, so it can be used to recognize abnormal walking pattern such as stumbling [6,8]. The energy of the signal can be computed as follows:

$$E_x = \int_{-\infty}^{\infty} |A(t)|^2 dt, \tag{3}$$

Tilt. When a user significantly tilts in a direction, he assumes an abnormal posture and this can lead to a fall. So, the user tilt can be a factor to assess the risk of a fall. User tilt can be estimated with the combination of gyroscope and accelerometer by means of a tilt vector [6–8]. The average of N instances of the acceleration data vectors is computed as follows:

$$\overrightarrow{B}(t) = \frac{1}{N} \Sigma_{t=1}^{N} \overrightarrow{A}_0(t) \tag{4}$$

The tilt angles are found as:

$$\theta_1 = \arctan\left(\frac{B_y}{B_z}\right), \theta_2 = \arctan\left(\frac{B_x}{B_y \sin(\theta_1) + B_z \cos(\theta_1)}\right) \tag{5}$$

The tilt acceleration is computed as follows:

$$\overrightarrow{A}_1(t) = \begin{bmatrix} \cos(\theta_2) & \sin(\theta_1)\sin(\theta_2) & -\cos(\theta_1)\sin(\theta_2) \\ 0 & \cos(\theta_1) & -\sin(\theta_1) \\ \sin(\theta_2) & \sin(\theta_1)\cos(\theta_2) & \cos(\theta_1)\cos(\theta_2) \end{bmatrix} \times \overrightarrow{A}_0(t) \tag{6}$$

The tilt gyroscope $\overrightarrow{G}_1(t)$ is computed similarly to $\overrightarrow{A}_1(t)$. Subsequently, the gravity vector is removed from the accelerometer data:

$$\overrightarrow{A}_2(t) = \left[\overrightarrow{A}_1 x(t), \overrightarrow{A}_1 y(t), \overrightarrow{A}_1 z(t) - \frac{1}{N} \Sigma_{t=1}^{N} \overrightarrow{A}_1 z(t)\right] \tag{7}$$

Finally, a general tilt vector is created by computing the magnitude of the horizontal acceleration and combining it with the measurement of the gyroscope.

$$\overrightarrow{A_h}(t) = \sqrt{A_{2x}(t)^2 + A_{2y}(t)^2},\ \overrightarrow{G_t}(t) = \sqrt{G_{1p}(t)^2 + G_{1r}(t)^2} \tag{8}$$

Energy and Hjorth parameters of the tilt vector are used as feature of the tilt to recognize the abnormal walking [6–8].

3 Proposed Features

In this section, six gait features are proposed. A group of five features are obtained from co-occurrence matrix and another feature is obtained from relative frequencies of different samples.

Co-occurrence Matrix Features. A co-occurrence matrix shows the scattering of similar adjacent values at a given offset. Normally, it is applied to images [16], but in this study it is used to analyze the acceleration and gyroscope values. In order to create the co-occurrence matrix of the data: first, the acceleration and gyroscope data are stored in a matrix. Each column of the matrix presents a sample in a specific time. Then, each couple of consecutive cells is analyzed to find the number of similar pattern in the whole matrix. Afterwards, the number of similar pattern is presented in the co-occurrence matrix with the index of cell contents. Let p_{ij} be the $(i, j)th$ element of the co-occurrence matrix divided by the sum of all the elements of the co-occurrence matrix. The following features are computed:

1. Contrast
   It is the measure of the intensity between a value and its neighbor cells over the entire obtained matrix:

$$Contrast = \sum_{i=1}^{K}\sum_{j=1}^{K}(i-j)^2 p_{ij} \tag{9}$$

2. Homogeneity
   It measures the spatial closeness of the distribution of the elements to the diagonal in co-occurrence matrix:

$$Homogeneity = \sum_{i=1}^{K}\sum_{j=1}^{K}\frac{p_{ij}}{1+|i-j|} \tag{10}$$

3. Correlation
   It shows how a value is correlated to its neighbor over the entire matrix:

$$Homogeneity = \sum_{i=1}^{K}\sum_{j=1}^{K}\frac{(i-m_r)(j-m_c)p_{ij}}{\sigma_r\ \sigma_c}\sigma_r \neq 0; \sigma_c \neq 0 \tag{11}$$

where m_r, m_c, σ_r and σ_s are computed as follows:

$$m_r = \sum_{i=1}^{K}\sum_{j=1}^{K} ip_{ij},\ m_c = \sum_{j=1}^{K}\sum_{i=1}^{K} jp_{ij} \tag{12}$$

$$\sigma_r = \sum_{i=1}^{K}\sum_{j=1}^{K}(i - m_r)^2 p_{ij},\ \sigma_c = \sum_{j=1}^{K}\sum_{i=1}^{K}(i - m_c)^2 p_{ij} \tag{13}$$

4. Uniformity
   It specifies the uniformity of elements in the co-occurrence matrix:

$$Uniformity = \sum_{i=1}^{K}\sum_{j=1}^{K} p_{ij}^2 \tag{14}$$

5. Maximum probability
   It measures the highest value of the co-occurrence matrix. Simply, it can be computed by $\max(p_{ij})$.

Standard Deviation of Relative Frequency. Relative frequency presents the distribution of the data. In order to compute the relative frequency, firstly, range of values are ordered in different intervals from minimum to maximum. Then, a histogram based on the repetition of the values is computed. Finally, relative frequency is computed by histogram divided by range of values. After computing the relative frequency, the standard deviation of the relative frequency distribution can be computed as a feature to classify the normal and abnormal walking.

4 Experimental Setup and Results

In this study, an experiment was performed with 22 users walking 10 s through two paths. The first path was along a flat area, while obstacles were put along the second path. Users couldn't look at obstacles and this can be a good simulation of abnormal walking [11].

In this section, firstly, proposed features of real-time data are analyzed on normal and abnormal walking then, different state-of-the-art approaches are implemented and evaluated. Analyzing the average values of features obtained from the co-occurrence matrix in normal and abnormal walking cases shows that *Homogenity*, *Uniformity* and *Correlation* of the normal walking are higher than the ones of the abnormal walking. On the contrary, the *Contrast* of the abnormal walking is higher than normal walking. Also, on average *Maximum* in normal walking is higher than in abnormal walking. Moreover, Fig. 1 shows the regression of the standard deviation of the relative frequencies. Since the standard deviation of abnormal walking is higher than normal walking in most of the cases, standard deviation of relative frequency can be a good classifier

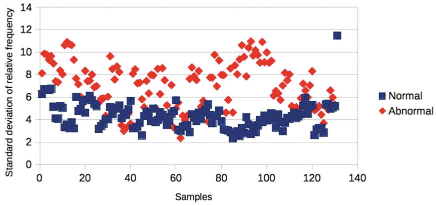

Fig. 1. Standard deviation of relative frequency.

for the normal and abnormal walking. In the following, combination of the co-occurrence matrix features and standard deviation of the relative frequency are used to classify the abnormal and normal walking. Two state-of-the-art methods are selected for a comparison. The first method [6] analyzes the tilt, and it is a basic algorithm exploited in future studies [7,8]. The second method [11] uses different acceleration features such as SMA, SMV, acceleration derivatives, peak-to-peak acceleration amplitude, and peak-to-peak acceleration derivative. The main classification methods of the abnormal and normal walking pattern are decision tree (DT) and support vector machine (SVM), and multilayer percepteron (MLP). For both algorithms different classifiers are evaluated and the best results are presented.

In this study, MLP with one hidden layer is used. Each neural node uses the following computation function:

$$CF = \phi(\sum_{i=1}^{n}(w_i x_i + b)), \tag{15}$$

where ϕ is the sigmoid activation function $\frac{1}{(1+e^{-x})}$, activation function helps to specify the output of node, w_i is the weight of each link, x_i is the input to the node, and b is the bias. Bias is a link with input one to the node.

Table 1. Results of different approaches.

Measures	Tilt	Acceleration	Proposed method
	DT	DT	MLP
Accuracy	83.88	81.42	90.82
Error rate	16.11	18.57	9.17
Sensitivity	0.88	0.78	0.87
Generality	0.21	0.15	0.06
Precision	0.81	0.83	0.93
Recall	0.88	0.78	0.87
F-measure	0.84	0.82	0.90
ROC area	0.86	0.82	0.96

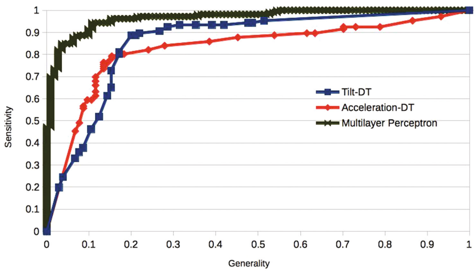

Fig. 2. ROC curves of different approaches.

The accuracy of the six proposed features with one layer MLP reaches 90.82%, which outperforms the other two state-of-the-art methods. Table 1 shows the result of different approaches.

The ROC curve is a graphical plot that illustrates the performance of a classifier [17]. The generality and sensitivity are plotted on x and y axes of the ROC plot, respectively. The best classifier is located at the top left corner of the ROC graph, which represents 100% sensitivity and 100% specificity.

The ROC curves allow to accurately compare the methods. As it can be seen in Fig. 2, the ROC curve of the proposed method outperforms the other two methods, because the area under the ROC curve of the proposed method is higher. Moreover, it increases the accuracy up to 7%.

5 Conclusion

This paper analyzed various fall factors and described corresponding features. New gait features based on acceleration data are proposed: five statistical features of the co-occurrence matrix and the standard deviation of relative frequency. Furthermore, state-of-the-art fall prediction algorithms have been experimentally evaluated. Based on the presented results, the proposed features in combination with a neural network present the best performance among the other fall prediction algorithms.

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