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Review Article

A Review on Fall Prediction and Prevention System for Personal Devices: Evaluation and Experimental Results

Masoud Hemmatpour, Renato Ferrero, Bartolomeo Montrucchio, and Maurizio Rebaudengo

Dipartimento di Automatica e Informatica, Politecnico di Torino, Italy

Correspondence should be addressed to Masoud Hemmatpour; masoud.hemmatpour@polito.it

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Injuries due to unintentional falls cause high social cost in which several systems have been developed to reduce them. Recently, two trends can be recognized. Firstly, the market is dominated by fall detection systems, which activate an alarm after a fall occurrence, but the focus is moving towards predicting and preventing a fall, as it is the most promising approach to avoid a fall injury. Secondly, personal devices, such as smartphones, are being exploited for implementing fall systems, because they are commonly carried by the user most of the day. This paper reviews various fall prediction and prevention systems, with a particular interest to the ones that can rely on the sensors embedded in a smartphone, i.e., accelerometer and gyroscope. Kinematic features obtained from the data collected from accelerometer and gyroscope have been evaluated in combination with different machine learning algorithms. An experimental analysis compares the evaluated approaches by evaluating their accuracy and ability to predict and prevent a fall. Results show that tilt features in combination with a decision tree algorithm present the best performance.

1. Introduction

Health centers have to deal with a large number of patients due to unintentional falls, resulting in huge cost on the society. For example, the average hospital cost for fall injury is over $ 30,000 [1]. Thus, there is a critical need for the development of cost-effective systems to reduce the injuries of a fall and to give faster assistance when a fall occurs. Several risk factors for falling can be identified, and specific interventions can be designed in order to reduce injuries. To this end, several systems were developed and are now available. Most of these systems concern fall detection [2–8], and they only notify user's acquaintances after a fall occurrence. However, there are systems with the goal of predicting and preventing a fall, called fall prediction and prevention systems (FPPSs) [9–13]. Such systems track and report data from wearable sensors without engaging the users in the monitoring process. FPPSs include sensors to collect data and software applications to process them: first, data are collected from sensors, then, the collected data are analyzed to extract an appropriate feature set. Afterwards, a machine learning algorithm is applied on the obtained data. Since smartphones nowadays are broadly used as personal digital assistance and they are equipped with precise sensors and communication component, they are used commonly in FPPSs as a monitoring device to collect data.

Fall prediction systems typically estimate real-time or future fall risk. These systems are helpful in reducing the financial and health consequences of a fall. Since both prediction and prevention systems evaluate a fall risk sometimes prediction and prevention terms are interleaved. These systems are essential to check the feasibility of performing recovery mechanisms before a fall occurrence.

Real-time fall prediction system aims to identify an abnormal gait pattern in order to estimate the probability of a real-time fall occurrence [14–16]. In real-time fall risk prediction, data are collected from sensors, and are analyzed to compute the appropriate feature set. Then, the risk of a possible fall is evaluated through classification algorithms. Real-time systems continuously assess the fall risk while the user is doing his/her daily activity. When an abnormal gait is

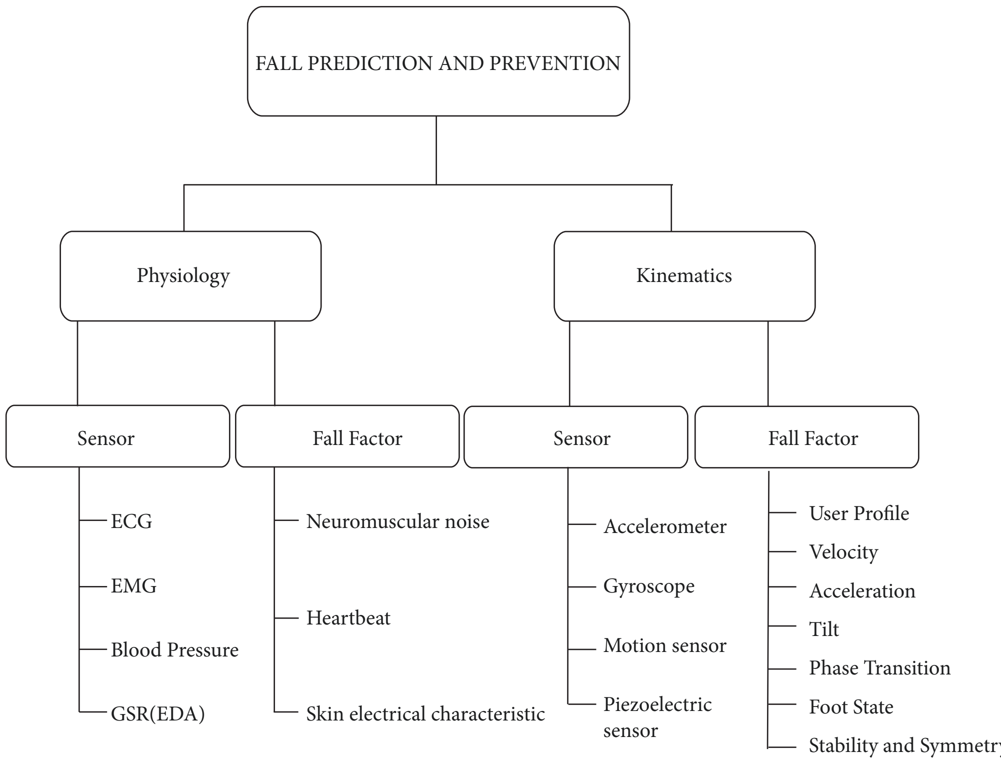

Figure 1: Fall prediction and prevention taxonomy.

detected then the user is alerted [14–16], or an external aid, such as a walker or robot, is exploited to prevent a probable fall [17, 18].

Future fall prediction is estimated through some clinical assessment tests. Probable future falls are prevented through improving gait and mobility by some exercises [17, 18]. These tests often involve questionnaires or functional assessments of posture, gait, cognition, and other risk factors. These clinical tests are subjective and qualitative and typically use threshold assessment scores to categorize people as fallers and nonfallers. Typically, these tests are timed up and go (TUG) [19], Berg Balance Scale (BBS) [20], sit to stand (STS) [21], and one leg stand (OLS) [22] to evaluate balance and lower limb strength.

The design of a fall prediction and prevention system faces several significant challenges. They need to be accurate, reliable, robust, and cost-effective [1]. In this paper, a fall prediction and prevention system is described in three parts: fall factors (i.e., fall symptoms), their features, and machine learning algorithms. This paper investigates every mentioned stage and experimentally evaluates the various approaches. This paper does not present systems using sensors such as camera and sound since they are prone to violate individual's privacy comparing to kinematic wearable sensors. In this paper, accelerometer (for measuring the acceleration) and gyroscope (for measuring the angular rate around one or more axes of the space) are considered for evaluation. These sensors are chosen since they are easily accessible and do not disturb the privacy of the user. The main contributions of this paper are the following:

(i) A comprehensive discussion on fall prediction and prevention systems

(ii) Preparing a dataset with realistic parameters to simulate abnormal gait

(iii) Finding the most representative fall factors

(iv) Evaluation of the fall factors based on the extracted feature on commonly used machine learning algorithms

This paper is organized as follows. In Section 2, existing FPPSs are classified according to the fall factors. Then, in Sections 3 and 4, feature extraction techniques and machine learning algorithms are described. Evaluation criteria are illustrated in Section 5. Afterwards, experimental results are shown in Section 6. Finally, conclusions are presented in Section 7.

2. Classification of Fall Factors

Fall prediction and prevention is a multifaceted problem that can be broadly categorized into two different domains: physiology and kinematics, as can be seen in Figure 1.

Physiological solutions consider intrinsic fall factors, i.e., parameters which mostly originate from the body. These solutions entail an in-depth medical evaluation of the risk factors and exploit sensors related to body monitoring:

(i) Electrocardiogram (ECG) sensor

Typically, ECG is used to assess the electrical and muscular operations of the heart but ECG sensing can also determine abnormalities that might lead to a fall [23, 24].

(ii) Electromyography (EMG) sensor

EMG is a technique for evaluating the electrical potential produced by muscle cells. EMG in combination with other medical sensors is used in FPPSs [23].

(iii) Blood pressure sensor

Blood pressure sensing is a physiological sign that can be investigated to determine abnormalities that may lead to a fall [23].

(iv) Galvanic Skin Response (GSR) sensor

GSR is a method for measuring the electrical characteristics of the skin. GSR in combination with ECG and EMG are used to predict and prevent falls [23].

Fall factors in physiological analysis are as follows:

(i) Neuromuscular noise

The increased neuronal noise associated with aging increases gait variability and consequently fall risk [25].

(ii) Heartbeat

An irregular heartbeat increases the risk of a fall [23, 26].

(iii) Skin electrical characteristic

Since the sweat glands are controlled by the sympathetic nervous system, which controls also emotions, a variation of the skin electrical characteristic could demonstrate a state of stress, which indicates the risk of a fall [23].

Unlike physiological solutions, kinematics-based FPPSs consider user's posture or gait variables. These solutions usually exploit movement sensors to investigate the extrinsic parameters of fall, i.e., characteristics of the movement of the body:

(i) Accelerometer

An accelerometer is a device that measures acceleration, i.e, the rate of change of the velocity of an object.

(ii) Gyroscope

A gyroscope gives the angular rate around one or more axes of the space. Angular measurement around lateral, longitudinal and vertical plane are referred to as pitch, roll and yaw, respectively. Typically, in FPPSs, the gyroscope is used in combination with an accelerometer.

(iii) Motion sensor

A motion sensor detects the movement of an object in the environment.

(iv) Piezoelectric sensor

A piezoelectric sensor measures the variations in pressure and force using the piezoelectric effect and converts them into an electrical charge.

Kinematic-based FPPSs focus on future or real-time fall occurrence. Future fall solutions evaluate a user to estimate his/her fall risk: if the fall risk is high, a probable future fall can be prevented through some exercises [27]. In contrast, real-time fall solutions avoid a fall while the user is doing his/her daily activity by alerting the user [14–16] or using an external aid such as a walker or robot [17, 18].

As extrinsic fall factors are among the most common causes of fall, this study surveys kinematic-based FPPSs, considering in particular data acquired with gyroscope and accelerometer sensors. The main kinds of factors in kinematic analysis which can increase the risk of fall in FPPSs are explained in the following.

2.1. User Profile. User profile can affect the fall risk. For example, the risk of a fall for elderly people is higher than young people, and the risk of a fall is higher in people who experienced a previous fall. Fall risk can be assessed through a weighted generic formula that combines all these factors [28].

2.2. Velocity. People with increased fall risk tend to walk slowly. As such, the actual fall risk can be quantified according to gait speed [29]. Gait speed is estimated by measuring duration and length of user's steps. The step duration is calculated as the time between two consecutive foot contacts. The step length is calculated as the sum of the displacement during the swing phase and the stance phase.

2.3. Acceleration. Changing of body movement in a prefall state causes alternation in the acceleration, so by processing the Acceleration Time Series (ATS), a fall event can be predicted. As Figure 2 illustrates, human motion during the time period S can be presented with n smaller periods T_s [30]. Period T_s itself consists of m short periods T with m acceleration samples. Basically, ATS is characterized by a series of elements c_i over time, where each element describes the feature of the movement during period T_s.

2.4. Tilt. Tilt is inclination from horizontal or vertical line. When a user significantly tilts in a direction, it shows an abnormal posture, which can lead to a fall. So, the user tilt can be a factor to assess the risk of a fall. Table 1 illustrates the notations to measure user's tilt [14–16].

Some traditional standard balance tests, such as sit to stand (STS), uses trunk tilt to evaluate the risk of a fall. The trunk tilt is calculated based on the angles between the sensor and the horizontal line of the ground [31].

2.5. Postural Transition Duration. Posture specifies the position of the body. Any activity begins with a posture and ends with another posture. Postural transition duration specifies the duration of a transition from a posture to another one. Balance control and stability of the body during postural transitions are key factors for avoiding falls. Postural transition duration can be an indicator of fall because it is significantly correlated with the fall risk [31]. Higher transition duration means lower muscle strength, and consequently higher fall risk. The duration of the postural transition can be computed by means of the accelerometer and gyroscope by measuring

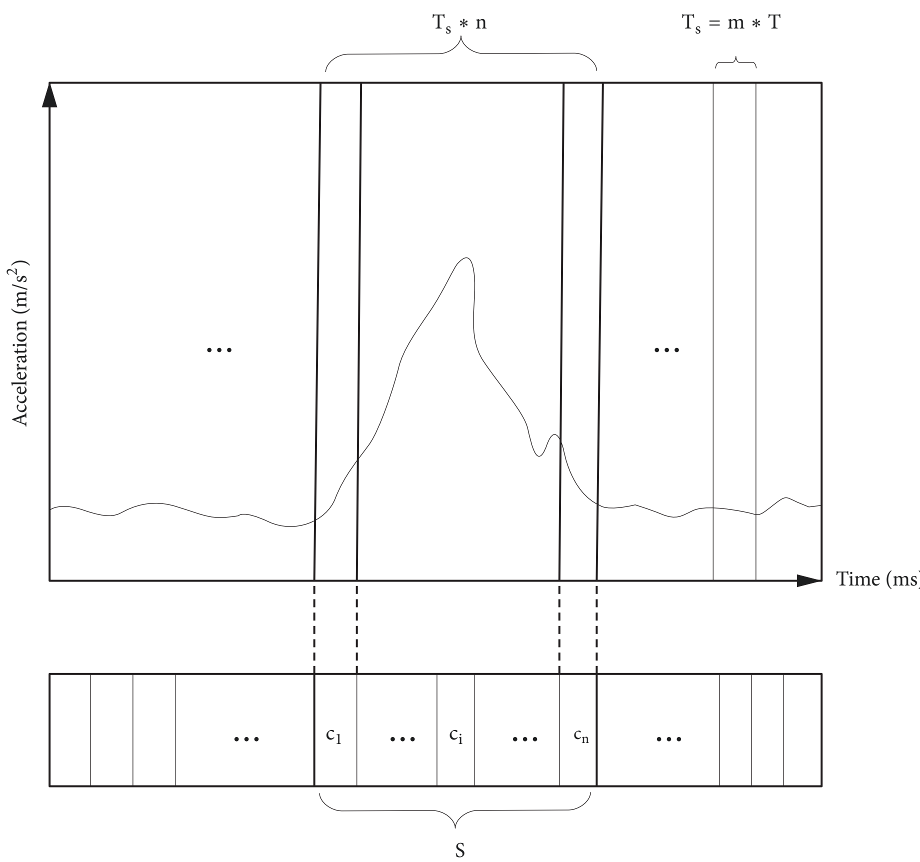

Figure 2: ATS accelerometer.

Table 1: Results of different approaches with decision tree and support vector machine classifications.

Measures	Tilt		Speed		Acceleration	
	DT	SVM	DT	SVM	DT	SVM
Accuracy	*83.88*	65.7	72.11	61.53	*81.42*	56.66
Error Rate	16.11	34.2	27.88	38.46	18.57	43.33
Sensitivity	0.88	0.74	0.87	0.66	0.78	0.26
Generality	0.21	0.42	0.43	0.43	0.15	0.12
Precision	0.81	0.63	0.67	0.60	0.83	0.68
Recall	0.88	0.74	0.87	0.66	0.78	0.26
ROC Area	0.86	0.65	0.69	0.61	0.82	0.57

the depression on the vertical axis acceleration signal, and the positive and negative angular rotations of the horizontal axis. The depression of the acceleration signal comes from the movement of the body, and the angular rotation is due to the forward and backward leans of the trunk during transition.

2.6. Foot State. The foot state indicates the posture of the foot during the gait cycle. Since foot state can specify the balance of the user, investigating the foot state can help to define the prefall state and estimate the fall risk. Some FPPSs focus on features related to foot state such as foot clearance (i.e., the distance of the foot and ground during walking) and foot age (i.e., relation of the age with the foot pressure) [32, 33].

2.7. Stability and Symmetry. Stability means the resistance of standing against a position change. Symmetry is the balance of the pressure on two feet. Stability and symmetry affect the functionality of the user gait: a gait with weak stability and symmetry has a higher fall risk. According to the stability and symmetry of gait, an assessment model can be used to predict the fall risk [34].

3. Feature Extraction

After acquiring signals from sensors, a feature extraction technique should be applied to extract appropriate information. Since data collected from sensors contain undesired information, filtering techniques are essential. A filtering

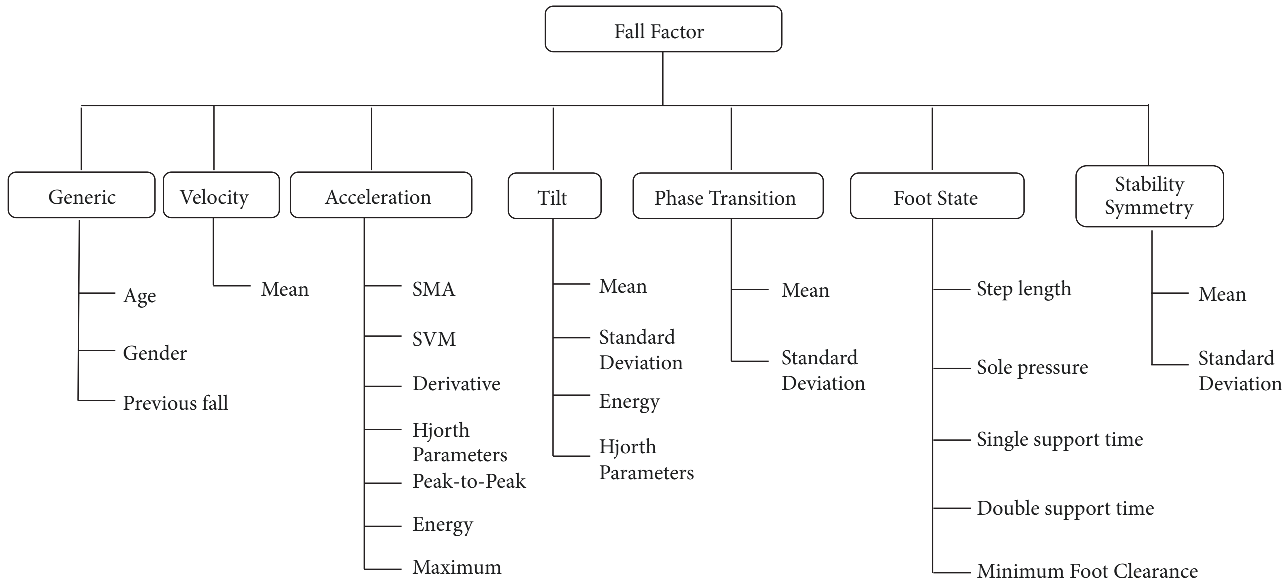

Figure 3: Fall factors approaches.

technique eliminates some frequencies from the original signal to attenuate the background noise and to remove undesired frequencies [29, 35]. Frequently used filters in FPPSs are high-pass filters, which eliminate frequencies lower than the cutoff frequency, and low-pass filters, which pass only frequencies lower than a certain threshold frequency. After filtering the collected data, appropriate features should be selected. Since analyzing a high number of features requires a large amount of memory, finding the optimal feature set can improve the performance of the system. The main features extracted from each fall factor are listed in Figure 3 and described in the following.

3.1. User Profile. Falls are the result of a combination of factors involving age, sex, mobility, daily activity, cognition, and previous fall. Thus, fall risk can be expressed as a simple function of user profile features with appropriate weights [28]:

$$\begin{aligned} Fall\ Risk = {} & 0.13\left(I_a\right) + 0.15\left(I_s\right) + 0.14\left(I_m\right) \\ & + 0.1\left(I_{adl}\right) + 0.18\left(I_c\right) + 0.33\left(I_f\right) \end{aligned} \tag{1}$$

where

(i) I_a is the age index: the risk of falls in the elderly is assumed increasing with age [36];

(ii) I_s is the sex index: female gender is associated with greater risks of fall [37];

(iii) I_m is the mobility index: mobility implies the ability to move from place to place which can be indicator of a fall [38, 39];

(iv) I_{adl} is the index derived from the activities of daily living (ADL): fall risk and a person's perception of capabilities within a particular domain of activities have strong independent correlation with ADL [40];

(v) I_c is the cognition index: impaired cognition and dementia independently predict falls [41];

(vi) I_f is the previous fall index: a history of previous falls has been recognized as being a significant risk factor for future falls [41].

The weights in the above formula and the choice of indices are made by statistical result of the earlier study [28]. The weights differ for male and female; in the above formula weights are calculated for female gender.

3.2. Velocity. As mentioned in Section 2.2, low gait speed increases the risk of a fall. The average speed of the gait can be measured to estimate the fall risk [29].

3.3. Acceleration. Frequently used features of the acceleration are described in the following. In the formulas, $A(t)$ refers to the acceleration and $A_x(t)$, $A_y(t)$, and $A_z(t)$ indicate the components of the acceleration in the 3 axes. Moreover, A_{xi}, A_{yi}, and A_{zi} are the i-th acceleration samples in the 3 axes.

The Signal Magnitude Area (SMA) can be used as a feature of the acceleration signal to classify the activities of the user [35]. SMA is computed as follows:

$$\begin{aligned} SMA = {} & \frac{1}{T}\left(\int_0^T \left|A_x(t)\right| dt + \int_0^T \left|A_y(t)\right| dt \right. \\ & \left. + \int_0^T \left|A_z(t)\right| dt\right) \end{aligned} \tag{2}$$

where T is the length of measurement time.

The Signal Magnitude Vector (SMV) is one of the common measures to calculate the resultant of the signal:

$$SMV = \frac{1}{n}\sum_{i=1}^{n}\sqrt{A_{xi}^2 + A_{yi}^2 + A_{zi}^2} \tag{3}$$

SMV demonstrates the degree of the movement intensity and it is an essential metric in FPPSs [15, 16, 30, 35].

Moreover, the derivative ($A'(t)$) of the acceleration indicates the vibration of the movement and can be used as an acceleration feature [35].

Hjorth parameters are statistical features of the signal in time domain [42]. They are based on the variance of the signal $var(A(t))$:

(i) $Hjorth\ activity = var(A(t))$; it can indicate the signal power.

(ii) $Hjorth\ mobility = \sqrt{var(A'(t))/var(A(t))}$; it can be an indicator of the smoothness of the signal curve.

(iii) $Hjorth\ complexity = mobility(A'(t))/mobility(A(t))$; it can effectively measure irregularities in the frequency domain.

The Hjorth parameters are mostly used to analyze the electroencephalography signals but they are also utilized to analyze accelerometer and gyroscope signals in FPPSs [15].

Peak is the absolute maximum value of the signal over the period of time, and peak-to-peak is the difference between the minimum and the maximum value of the signal over the period of time. The peak-to-peak acceleration amplitude and the peak-to-peak acceleration derivative are two features used in FPPSs [29].

The energy of the acceleration signal describes the amount of physical 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 [14, 16]. The energy of the signal can be computed as

$$E_x = \int_{-\infty}^{\infty} |A(t)|^2 \, dt, \tag{4}$$

As described in Section 2.3, ATS can be characterized by a series of features c_i. Feature c_i can be determined by calculating the resultant acceleration $\overrightarrow{A_F}$:

$$\overrightarrow{A_F} = \sqrt{\overrightarrow{|x|^2} + \overrightarrow{|y|^2} + \overrightarrow{|z|^2}} \tag{5}$$

The resultant acceleration ($\overrightarrow{A_F}$) varies within a small range B $= [b_1, b_2]$ around g where g is the gravity force, $b_1 < g < b_2$. Therefore, if the resultant acceleration exceeds B, an abnormal walking is probable.

3.4. Tilt. Trunk tilt has an important role in the maintenance of the posture. The average and standard deviation of trunk tilt are measured during the sit to stand phase of STS test to assess the risk of a fall [31]. Moreover, energy and Hjorth parameters of the tilt vector are used as an indicator of the abnormal motion [14–16].

3.5. Postural Transition Duration. The average and standard deviation of the duration of the postural transition can be used to estimate the user's fall risk [27, 31].

3.6. Foot State. Step length is a feature of the foot in a gait cycle that can be a good indicator of the fall risk. Since a high step length decreases the stability of the user, the fall risk increases as the length of the step grows. Single support time is the time when only one limb is on the ground in a gait cycle. Double support time is the time spent when both feet are on the ground in a gait cycle. The foot age is an index of the gait which shows how old is the gait condition of the subject. Through the foot age, the falling risk can be quantified. The foot age is computed through the four gait features (step length, step center of sole pressure (CSP), distance of single supporting period, and time of double support period) [32].

The Minimum Foot Clearance (MFC) is another foot state feature that indicates the vertical distance between the lowest point of the foot of the swing leg and the walking surface during the swing phase of the gait cycle. The foot clearance is an important gait parameter that is related to the risk of falling. The low foot clearance for a step during the walking increases the probability of fall because of hitting to an obstacle. The foot clearance is extensively studied to detect trips and falls [33, 43, 44].

4. Machine Learning Algorithm

Features extracted from the input signals are processed by a machine learning algorithm in order to classify the abnormal behavior and the normal daily activity. Exploited machine learning algorithms in FPPSs are described in following.

(1) *Threshold-based Algorithm* utilizes a threshold to classify the feature set of the user gait. After extracting the desired features from the input signals, these features are compared with predefined thresholds. Since the thresholds have an important effect on the performance of the algorithm, the biggest challenge of a threshold-based algorithm is determining the thresholds. Moreover, the performance of the algorithm depends on the number of features which need to be analyzed. However, complexity and power consumption of this type of algorithms are low, so it can be adequate for devices with limited resources. Some examples of different FPPSs that exploit a threshold-based algorithm are described in the following.

Features of the acceleration signal of human upper trunk [30] in a short time interval before the fall are denoted as λ. After obtaining the ATS of the user, P(ATS $|\lambda$) states the probability of a fall occurrence during the user motion. Two thresholds P1 and P2 are specified to predict and detect a fall. As Figure 4 illustrates, the output of P(ATS $|\lambda$) is an input to the algorithm. Then, based on predefined thresholds, if P is higher than P1, the fall risk is notified, if P is higher than P2, a possible fall is noticed.

SMV, SMA, peak-to-peak, and derivative of acceleration signals are computed as feature set of user gait [35]. Afterwards, thresholds are determined to define a near fall state.

The gait status can be classified based on mean and standard deviation of stability and symmetry [34]:

(i) If index ≤ mean+std, then the gait status is normal: the subject walks normally and there is not fall risk.

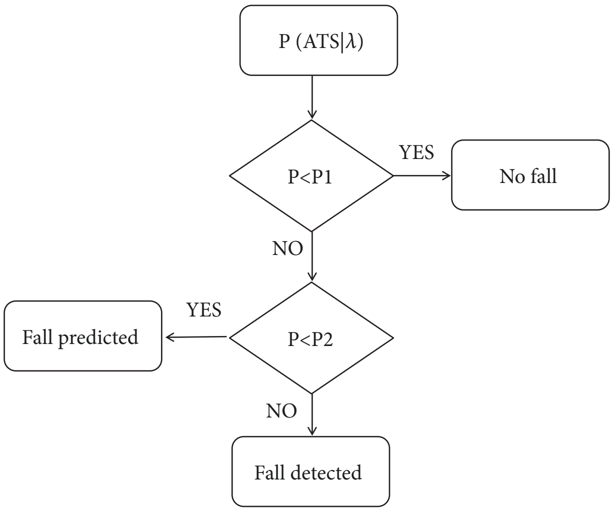

Figure 4: Threshold-based algorithm.

(ii) If mean+std < index ≤ 3∗mean, then the gait status is attentive: the subject needs to care when walking.

(iii) If index > 3∗mean, then the gait status is dangerous: the subject should present a risk to fall.

(2) *Decision Tree* (DT) is a directed tree with a root node without incoming edges and all other nodes, known as decision nodes, with one incoming edge and possible outcoming edges; a leaf node is a node without outcoming edges. At the training stage, each internal node splits the instance space into two or more parts. After that, every path from the root node to a leaf node forms a decision rule to determine which class a new instance belongs to [45]. Each internal node represents a test on an attribute or on a subset of attributes, and each edge is labeled with a specific value or range of values of the input attributes. DT is a fast algorithm but the computation cost on the tree grows as the size of the tree increases.

Figure 5 illustrates how a decision tree algorithm can be used in the classification of normal and abnormal walking [14–16]. Firstly, accelerometer and gyroscope signals are collected, then a general tilt vector is computed. Afterwards, appropriate features (e.g., energy; Hjorth parameters) are calculated from tilt vector. Then, DT is used to determine the abnormal walking.

(3) *Support Vector Machine* (SVM) finds the best hyperplane with the maximum margin to separate two classes. SVM can be defined as linear or nonlinear according to the kind of hyperplane function. SVM is a prevailing classification model for gait pattern recognizing [46–48]. SVM can be used to determine the threshold value to classify the user gait [30].

(4) *Fuzzy Logic* defines a membership function in order to assign to objects a grade of membership ranging between zero and one. For example, if X is a class of objects, with a generic element denoted by x, a fuzzy set A in X is characterized by a membership function $f_A(x)$. The value of $f_A(x)$ represents the "grade of membership" of x in A, which is a real number in the interval $[0, 1]$. The nearer the value of $f_A(x)$ to unity, the higher the grade of membership of x is in A [49].

Based on the relationship between fall risk and age, the fuzzy logic is used to prevent a fall using the sole pressure sensor to estimate the age [32]. Firstly, the fuzzy membership function for young age, μ_Y, middle age, μ_M, and elderly age, μ_E, are calculated based on the four extracted features (step length, step center of sole pressure width, distance of single supporting period, and time of double support period) of the user gait. Then, a fuzzy logic is used to estimate the foot age.

5. Evaluation Criteria

Evaluation criteria of a machine learning algorithm are described in the following. In all presented formulas, P and N represent the total number of positive and negative instances. A positive and negative instance can be defined as an abnormal/normal walk. True Positive (TP) and True Negative (TN) are defined as correct identification of a true classification of positive and negative instance, respectively. False Positive (FP) and False Negative (FN) misidentify positive and negative instances, respectively.

(1) *Specificity* or *True Negative Rate* (TNR) measures the rate of negative instances that are correctly identified as negative:

$$Specificity = \frac{\#TN}{\#TN + \#FP} \tag{6}$$

Moreover, *Generality* is computed as 1 - *Specificity*.

(2) *Sensitivity* or *True Positive Rate* (TPR) measures the rate of positive instances that are correctly identified as positive:

$$Sensitivity = \frac{\#TP}{\#TP + \#FN} \tag{7}$$

(3) *Accuracy* of an algorithm computes the number of samples correctly classified:

$$Accuracy = \frac{\#TP + \#TN}{\#P + \#N} \tag{8}$$

(4) *Error rate* is the number of wrong classifications:

$$Error\ Rate = \frac{\#FP + \#FN}{\#P + \#N} \tag{9}$$

(5) *Precision* is the percentage of the samples correctly classified as true:

$$Precision = \frac{\#TP}{\#TP + \#FP} \tag{10}$$

(6) *Recall* is the percentage of truly classified positive samples:

$$Recall = \frac{\#TP}{\#TP + \#FN} \tag{11}$$

It should be noted that one criterion alone may not be sufficient to evaluate the algorithm.

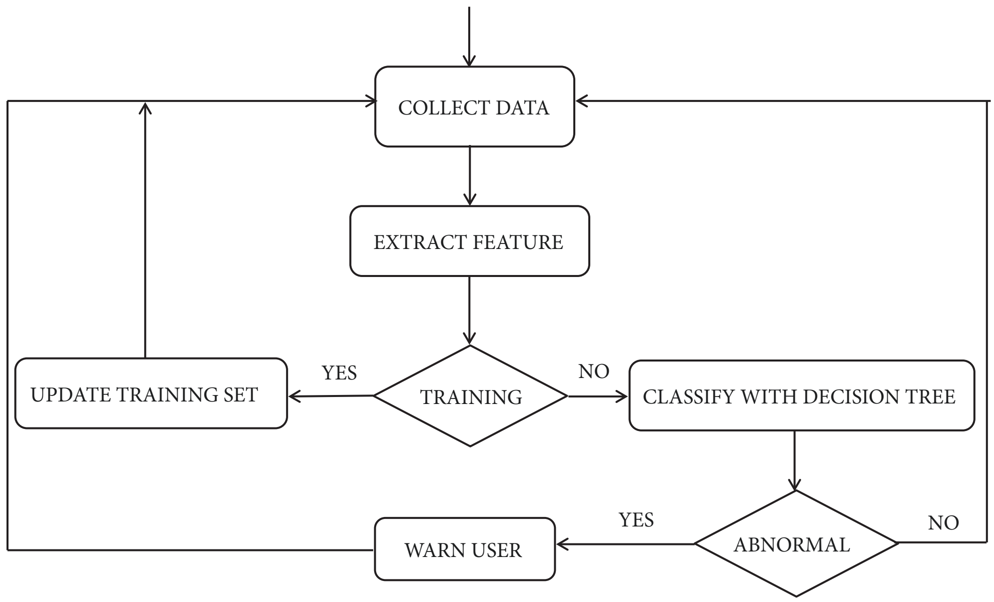

Figure 5: Fall prediction and prevention algorithm based on decision tree.

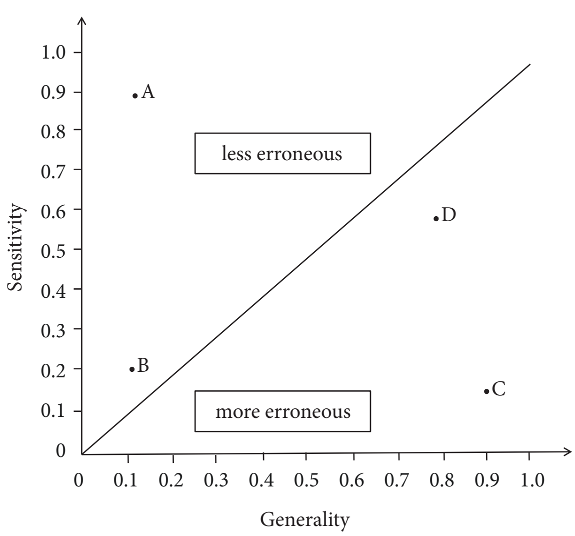

Figure 6: ROC plot of classifiers.

The Receiver Operating Characteristic (ROC) curve can be used to compare different algorithms. The ROC curve is a graphical plot that illustrates the performance of a classifier [50]. 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 diagonal line from the left bottom to the top right corner divides the ROC space into two parts. The space above the diagonal represents classification with few errors, while the space below the line shows more erroneous results. For example, Figure 6 compares four possible algorithms: A(0.1,0.9), B(0.1,0.22), C(0.9,0.15), and D(0.8,0.6). A has the best prediction among the four instances. The further the result is from the diagonal in the above space, the better the accuracy is. C is the worst among the four instances, because it is below and far from the diagonal line. B is a good classifier but not as much as A, because it is above but not far from the diagonal line. Moreover, since D is closer to diagonal line, it is more acceptable than C.

To show how ROC curve is plotted, the output of two classifiers is illustrated in Figure 7. The x-axis shows the probability that the user gait is abnormal, and the y-axis represents the number of instances with the same probability. For instance, point (0.8, 5) means that the gait of 5 users is predicted as abnormal with probability 0.8, and the gait of all users is abnormal because it is located along the abnormal distribution. To prepare the ROC curve, firstly, a random variable X is defined and a threshold (T) is set. Everything above the threshold ($X > T$) is classified as abnormal and below the threshold ($X < T$) as normal. Then, sensitivity and generality of this classification with threshold T are computed. To generate the ROC curve, the sensitivity versus the generality for all possible thresholds should be plotted. Figure 7(a) shows a classifier with its associated ROC curve. Since the distributions of normal and abnormal cases barely overlap, the corresponding ROC curve of the classifier is close to the upper left corner of the plot. Figure 7(b) shows another classifier, where the distribution of normal and abnormal cases overlap almost completely, so the ROC curve of the classifier is close to diagonal line.

6. Experimental Results

In this section, the state-of-the-art FPPSs with accelerometer and gyroscope have been implemented and then compared according to the criteria described in Section 5.

First objective of the experiment is empirical comparison of fall factors to find the most representative one among

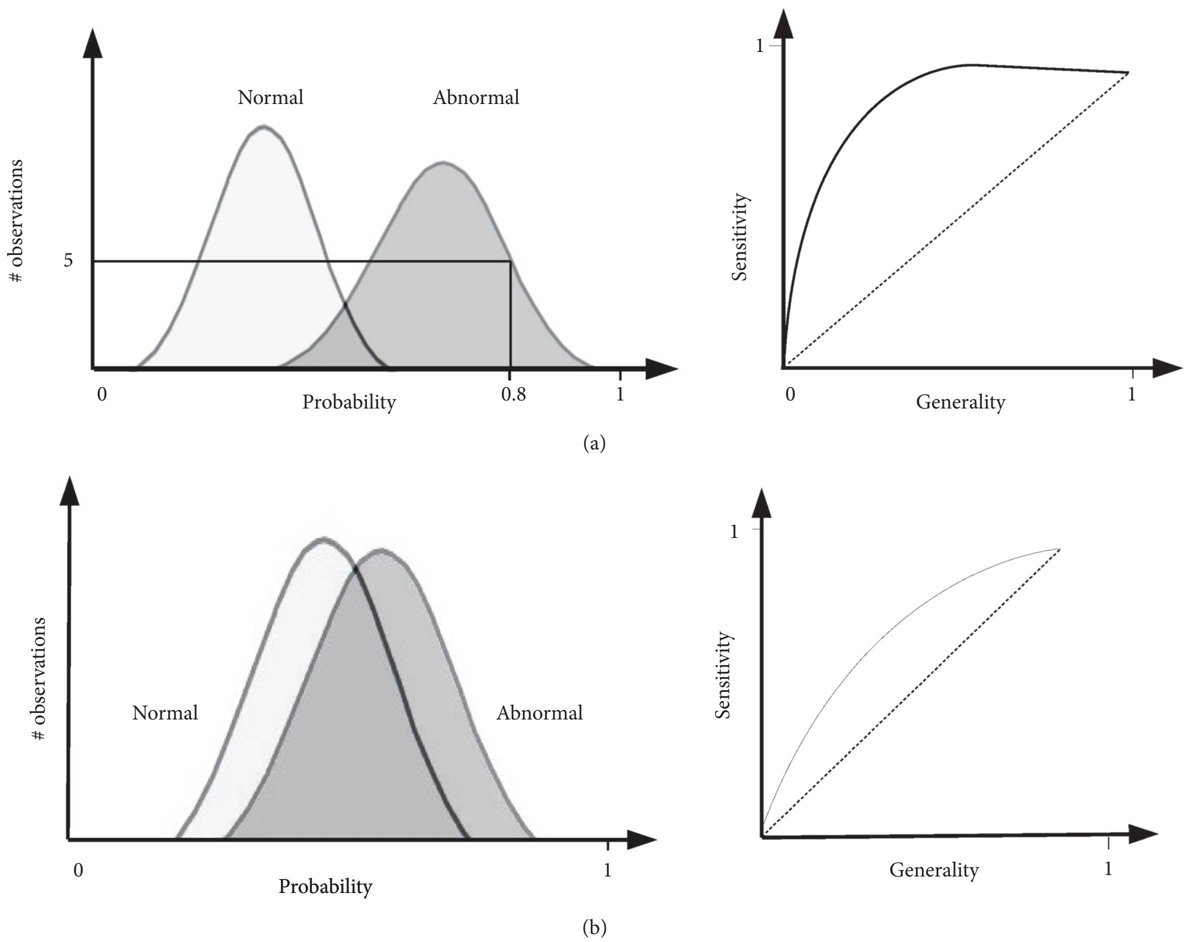

Figure 7: ROC of a good classifier (a) and poor classifier (b).

acceleration, tilt, and velocity. The second objective is evaluating different machine learning algorithm based on presented features for each fall factor in the presented dataset. It should be noted that the goal of the experiment is not finding an optimal feature set for each fall factor.

A fall occurs due to passive causes like weakness, balance deficit, gait deficit, visual deficit, and mobility limitation. The following are the most frequently used methods to simulate an abnormal gait, which can lead to a fall:

(i) Walking with straightened knee [14–16].

(ii) Walking with leg length discrepancy [14–16].

(iii) Walking on a rough surface [51].

(iv) Walking through obstacles [35].

In the experiments, an abnormal walk is modeled as irregular gaits obtained by walking through obstacles which can cause stepping, tripping, and stumbling. Thus, a flat area with different types of obstacles is prepared. Obstacles included empty boxes (height: 37 cm, length: 20 cm, and width: 17 cm) and plastic bottles (height: 20 cm; diameter: 6 cm), which are placed 60 cm far from each other.

Since the real falls cannot be experimented due to the risk of injury, only forward fall is simulated with protection. However, the applied method in this paper can easily be generalized to other type of falls (i.e., backward; lateral). Users are asked to walk through obstacles without looking them for 10 seconds. The users in the experiments are 19 men with weight in the range of 65-110 kg and height in the range of 160-185 cm and 3 women with weight in the range of 50-60 kg and height in the range of 157-165 cm. All users are without gait disturbances. Furthermore, users are in the range of 18-35 years old. Data is collected through MATLAB R2015b. WEKA tool version 3.6.13 (WEKA is an open source data mining tool that can be downloaded from http://www.cs.waikato.ac.nz/ ml/weka/) has been used to classify the obtained data.

An iPhone 4S is adopted in the experiments, equipped with the STMicro STM33DH 3-axis accelerometer and the STIMicro AGDI 3-axis gyroscope. Commonly adopted sampling frequencies range from some dozens to hundred of Hertz such that they are constant and higher than gait cycle frequency. In the experiment, the frequency is fixed to 10Hz. Since the body Center of Pressure (COP) reveals several information of user gait, the smartphone is placed on the lower back of trunk, near the real Center Of Mass (COM) position, assuming that this position moves parallel to the COP, and the same acceleration and positions will be measured [52].

In the following, velocity, acceleration, and tilt fall factors with different combinations of machine learning algorithms have been evaluated.

SMA, SVM, maximum derivative, Hjorth parameters, peak-to-peak, and energy features of acceleration are considered in the experiments. Moreover, mean, standard deviation, energy, and Hjorth parameters of tilt and mean of velocity are considered as the features in the experiment. The performance of different features with a particular machine learning algorithm was already presented in previous studies. The novelty of this paper is the comparison of different fall factors with presented features on different machine learning algorithm.

Table 1 shows the result of the experiments when the decision tree and support vector machine are selected to classify the obtained data. As reported in the last line of Table 1, a higher ROC area corresponds to a better accuracy. The comparison of the results from different fall factors shows that the tilt always has better accuracy among the other fall factors. Combination of tilt with decision tree gives 83.9% of accuracy and with support vector machines gives 65.7% of accuracy. So, the preciseness of tilt factor shows that it can be adopted as a deserved representative of fall factors in FPPSs implemented with personal monitoring device.

There are several factors that can affect the decision to choose a machine learning algorithm. In literature there are several studies which compare the performance of different machine learning algorithms [53–55]. The best machine learning algorithm cannot be universally identified because machine learning algorithms are task-dependent. In addition, the best machine learning algorithms for a particular task depends on several factors. The feature set is the primer factor which impacts on the performance. In addition, also dataset characteristic such as number of samples, type and kind of data, and skewed data can impact on the performance. In a skewed dataset, almost all samples fall in one particular class rather than in the other classes.

The comparison of the different machine learning algorithms with the presented setting in this paper shows that DT has better performance than SVM in all the combinations. Although DT has better performance comparing to the SVM, it cannot be generalized to all experiments and datasets. The reason is based on the no free lunch theorems that indicates there is not superiority for any machine learning algorithm over the others, so the best classifier for a particular task is task-dependent [56, 57]. However, it should be noted that DT requires more memory space when the size of the tree grows. Moreover, as Figure 8 shows, the tilt fall factor with DT algorithm has the best performance to detect abnormal walks, and speed has the lower performance. Since in the experiment patients tilt in a direction, it is not surprising that tilt is the most representative fall factor.

7. Conclusion

This paper analyzed different aspects of fall prediction and prevention systems. It provides a comprehensive overview of various fall factors and corresponding features. Moreover,

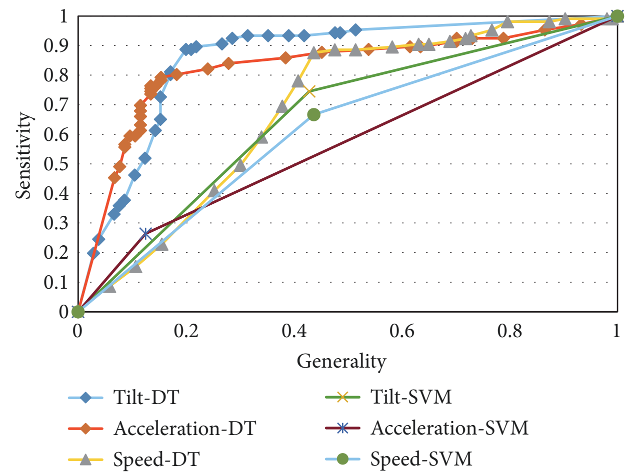

Figure 8: ROC on different approaches of 22 users with 110 samples.

different machine learning algorithms in fall prediction and prevention systems have been reviewed. Furthermore, multiple combinations of features and fall prediction and prevention algorithms have been experimentally evaluated to find an optimal solution. Based on the presented results tilt features in combination with the decision tree algorithm present the best performance among the other permutations of fall factors and fall prediction and prevention algorithms.

Future work may include

(i) generalizing the dataset to older adults or patients with neurological disorders;

(ii) adopting new machine learning algorithms in the comparison list;

(iii) comparing systems across other performance metrics such as time, accuracy with respect to the size of dataset, number of features, memory consumption, and power consumption.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this article.

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