An Efficient Design of a Machine Learning-Based Elderly Fall Detector

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Abstract. Elderly fall detection is an important health care application as falls represent the major reason of injuries. An efficient design of a machine learning-based wearable fall detection system is proposed in this paper. The proposed system depends only on a 3-axial accelerometer to capture the elderly motion. As the power consumption is proportional to the sampling frequency, the performance of the proposed fall detector is analyzed as a function of this frequency in order to determine the best trade-off between performance and power consumption. Thanks to efficient extracted features, the proposed system achieves a sensitivity of 99.73% and a specificity of 97.7% using a 40 Hz sampling frequency notably outperforming reference algorithms when tested on a large dataset.

Keywords: Elderly fall detection · Micro electro mechanical system
Inertial measurement unit · Support vector machine
Multi-layer perceptron · K-nearest neighbors

1 Introduction

In recent years, the number of old people is increasing rapidly [1]. One of the problems that often arise is the problem of falls. Moreover, old people would rather stay at home than live in some retirement home [1]. In these risky situations, it is very important to provide adequate interventions for the elderly when a fall occurs. Therefore, many devices have been developed to detect falls automatically. Fall detection devices can be divided into three categories: wearable, ambiance and camera based devices [2, 3]. The main drawbacks of ambiance and camera based devices are the expensive hardware costs and the fact that their usage is limited to indoor environments. Moreover, wearable devices commonly use inertial measurement units like accelerometers and gyroscopes as well as magnetometers or a fusion between different sensors in order to capture human movements. Thanks to the rapid development of the micro-electromechanical systems, wearable fall detection devices can be implemented as small, lightweight and low-cost devices [4].

Fall detection algorithms used in the literature can be divided into threshold-based and machine learning-based methods. One of the recent and efficient

threshold-based algorithms is the work by Pierleoni *et al.* [5] where authors designed and implemented a wearable fall detector with four sensors that are accelerometer, gyroscope, magnetometer and barometer. The first three sensors are used to estimate the orientation of the body. This is achieved depending on an efficient quaternion-based and low-computational complexity sensor fusion algorithm namely Madgwick's algorithm [6]. Once the orientation is estimated, it is used to rotate the acceleration vector from the sensor frame into the Earth frame. Then the Earth gravity vector (that is known in the Earth frame) is subtracted from the vertical acceleration component in order to get an initial estimate of the dynamic vertical acceleration of the body. The latter is then fused with the output of the barometer in order to achieve an accurate estimate of the dynamic vertical acceleration. This signal is then analyzed and multiple thresholds are applied in order to detect the fall. This algorithm proves its good performance in a variety of experimental scenarios. However, from the power consumption point of view which is a critical topic in designing a wearable device, using four sensors with a relatively complicated sensor fusion algorithm is not recommended as it affects the battery life considerably. The aforementioned drawbacks motivated researchers to use only a 3-axial accelerometer for capturing the human movements. In the present study, the proposed design of the fall detector is only based on an accelerometer. The total three dimensional acceleration $\boldsymbol{a} = [a_x \ a_y \ a_z]^{\mathrm{T}}$ measured by the accelerometer is a combination of the body acceleration $\boldsymbol{a}_{body}$ and the Earth gravity field $\boldsymbol{g}$. It is given as follows [7]:

$$\boldsymbol{a} = \boldsymbol{K}[\boldsymbol{C}_n^b(\boldsymbol{g} + \boldsymbol{a}_{body})] + \boldsymbol{b} + \boldsymbol{v} \tag{1}$$

where $\boldsymbol{K}$ denotes the scale factor matrix, $\boldsymbol{C}_n^b$ denotes the direction cosine matrix that represents the orientation of the navigation frame (frame n) with respect to the body frame (frame b), $\boldsymbol{b}$ represents the bias vector and $\boldsymbol{v}$ represents measurement noise. An interesting recent research by Abdelhedi *et al.* [8] proposed a 3-axial accelerometer-based fall detection system that uses multiple predefined thresholds in order to detect the fall. The sum vector magnitude Σ given by Eq. (2) is used as a characteristic signal that is compared with two predefined amplitude thresholds in order to detect the free fall phase and the impact phase respectively, while the body tilt angle θ defined by Eq. (3) is used to detect the inactivity phase when the impact phase is detected:

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

$$\theta = \arctan \sqrt{a_y^2 + a_z^2}/a_x \tag{3}$$

This is achieved by comparing the tilt angle with a predefined threshold also. Although the simplicity of the aforementioned algorithm makes it attractive to be embedded in a wearable fall detector, using constant thresholds leads to a significant amount of false alarms because of the similar behavior of some Activities of Daily Living (ADLs) and falls. One more complicated but more

accurate methodology is to use machine learning techniques instead of the pre-defined threshold-based ones. Mezghani *et al.* [9] proposed a fall detection algo-rithm based on Support Vector Machine (SVM). Some statistical features are extracted from the motion signal that is acquired using a 3-axial accelerometer. These features are the mean, the minimum, the maximum, the range and the skewness calculated in a time window of a predefined width (see Fig. 1). Features extracted from a training dataset together with the corresponding ground truth (falls/ADLs) are used to learn the SVM. In the practical application, the on-line extracted features represent the inputs of the trained SVM that in turn makes a binary decision of a fall/ADL event. This algorithm achieved high accuracy in detecting falls. However, the false alarm rate needs to be further reduced.

Performance of fall detectors is evaluated in terms of both the successfulness in detecting falls when they occur and the absence of false alarms when no fall is present. These performance criteria are called the sensitivity and specificity respectively. To satisfy these criteria, an efficient machine learning-based fall detection system is proposed in this paper. Moreover, as the power consumption is a critical issue in designing a wearable device, both the sampling frequency and the hardware complexity are taken into account in the system we propose. Particularly, the motion is captured using the accelerometer only leading to a simple and low power consumption hardware design. In addition, as it is well known, lower sampling frequencies lead to lower power consumption. Conse-quently, the performances of the proposed system as well as the reference ones will be analyzed as a function of the sampling frequency in order to determine the best trade-off between performance and power consumption.

The rest of the paper is organized as follows: Sect. 2 describes the proposed methods while Sect. 3 is devoted to the experimental results and Sect. 4 concludes the paper and states the future work.

2   Methods and Materials

In classical supervised machine learning-based methods, the acquired signals are buffered for a predefined time period (called window) and then described within this window by extracting the signal features. These features are used together with the corresponding ground truth (fall/ADL in our case) to train the machine. In practical application, the features are extracted from the lat-est window and applied to the already trained machine that in turn makes its decision (fall/ADL). The proposed approach is based on supervised machine learning with two main contributions: (1) the efficient extracted features and (2) the novel training strategy. These two contributions as well as the proposed fall detection strategy are discussed in the following sub-sections.

2.1   Features Extraction

The key factor underlying the behavior of the machine learning-based methods is the efficiency in building the features that describe the raw signal. Particu-larly, the features vector is preferred to be as short as possible and as much
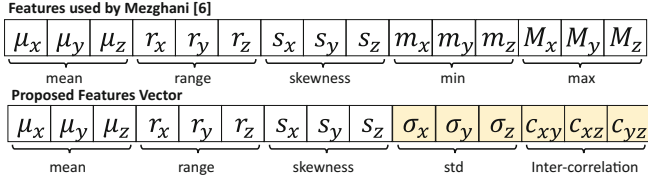
Features used by Mezghani [6]

μ_x	μ_y	μ_z	r_x	r_y	r_z	s_x	s_y	s_z	m_x	m_y	m_z	M_x	M_y	M_z
mean			range			skewness			min			max		

Proposed Features Vector

μ_x	μ_y	μ_z	r_x	r_y	r_z	s_x	s_y	s_z	σ_x	σ_y	σ_z	c_{xy}	c_{xz}	c_{yz}
mean			range			skewness			std			Inter-correlation		

Fig. 1. Proposed features vs. features used by Mezghani [9]

representative of the raw signal as possible. Although the performance of the SVM-based Mezghani algorithm [9] proves to be good, one can note that there is redundancy in the features vector. Particularly, the aforementioned algorithm uses the minimum and maximum values of the signal within the processed time domain and it also uses the range that is the difference between them. Therefore, the components of the features vector are not independent and thus not the best representative ones. To this end, we propose two better representative features than the minimum and maximum statistics. These features are the inter-correlation and standard-deviation. Inter-correlation between the accelerometer components is given by Eq. (4):

$$corr_{(x,y)} = cov(x,y)/(\sigma_x \times \sigma_y) \tag{4}$$

where $cov(x,y)$ is the covariance between x and y axes of the acceleration vector components and σ_x, σ_y are the standard deviations in the processed window. The idea underlying the usage of the inter-correlation feature is its ability to distinguish the activities which involve the movement in one dimension [10]. So, the extracted features employ the inter-correlations between the three components of the acceleration vector expecting a higher sensitivity with a significant reduction in false alarm rate in comparison with the considered reference algorithms that are the SVM-based Mezghani algorithm [9] and the threshold-based Abdelhedi [8] one. In summary, the proposed features vector consists of the mean, the range, the skewness, the standard deviation and the inter-correlation features where the first four features are calculated for all the accelerometer components (x, y and z) and the inter-correlations are calculated between x and y, x and z and y and z respectively. Figure 1 illustrates both the proposed features as well as the features used by Mezghani [9].

2.2   The Proposed Training Strategy

In the literature, most researches (if not all) use the same experimental conditions for both training and practical application. For example, the same sampling frequency for acquiring training data is used in the real application data acquisition. The proposed training strategy is to use optimal training conditions even

if they are computationally demanding as the training is made off-line and not on the wearable device. To this end, the proposed training strategy uses training data acquired with high sampling rates. In addition, the raw accelerometer data are smoothed using the Savitzky-Golay filter [11]. In the practical application, lower sampling rates are used and the aforementioned smoothing filter is not applied. This is in order to simplify the fall detection algorithm and to minimize power consumption. The theoretical justification of the proposed strategy is the fact that the objective of machine-learning is to capture the best nonlinear model that separates data classes ideally. That is why this training is better to be done in good conditions even if the practical application conditions are different. Three machine learning methods were explored with the proposed strategy in order to classify the activities into falls or ADLs (binary classification). These methods are the Support Vector Machine (SVM) with a linear kernel function, the K-Nearest Neighbors (KNN) and the Multi-Layer Perceptron (MLP).

2.3   Fall Detection Strategy

In the proposed fall detection strategy, the elderly activity is recorded and continuously buffered in overlapped sliding windows of a predefined width. The features extracted from the last window form the input of the trained machine. When the machine detects a fall, a counter is used to count the successive detections of the same fall. If the aforementioned counter exceeds a predefined threshold, the activity is considered as a fall. This strategy is useful to reduce the amount of false alarms making use of the large overlap between the successive windows. Moreover, as soon as a fall is detected, a beep is generated by the device and a counter is started. This is to give the elderly a capability to cancel the alarm if he/she can recover or if the alarm is just a false one. When the timer exceeds a predefined threshold, an alarm is sent to a medical team (or any authorized person) with the geographical position of the elderly.

3   Experimental Results

The performance of the proposed method is evaluated and compared with the reference SVM-based Mezghani algorithm [9] and the threshold-based Abdelhedi algorithm [8], applying the three following criteria: sensitivity, specificity and accuracy [12]. Experimental analysis is performed using a large reference open dataset, namely Sisfall [13]. In this dataset, the number of activities (falls and ADLs) files exceeds 4510 and are recorded on 37 subjects. All activities were acquired at the sampling frequency $F_s = 200$ Hz. From the aforementioned dataset, 16 ADL types which are the most common in elderly activities were selected for training together with 15 fall types gathered from 12 young subjects and 8 elderly ones. Numerically, the training set consists of 1864 samples
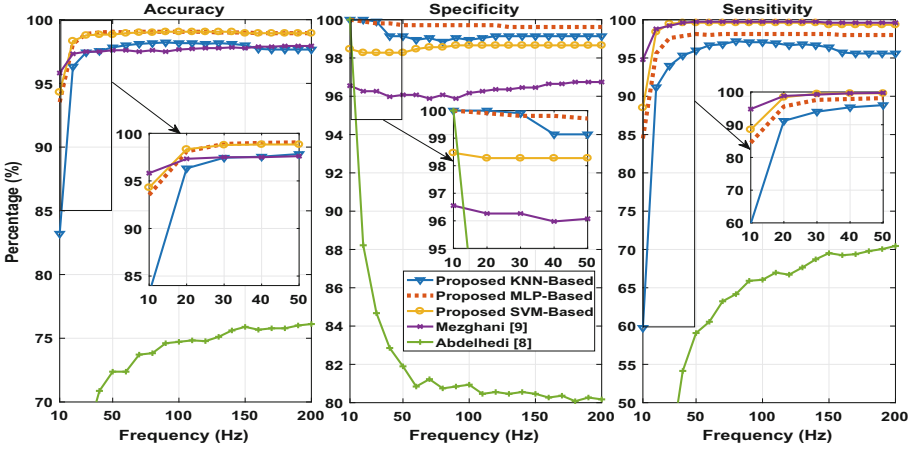
Fig. 2. The proposed KNN, MLP and SVM-based methods vs. the reference algorithms [8,9] in terms of accuracy, specificity and sensitivity for $F_s \in [10, 200]$ Hz

while the testing set consists of 1792 samples. Figure 2 illustrates the preliminary results using the aforementioned performance criteria as functions of sampling frequency. This frequency analysis is achieved by down-sampling the original signals $F_s \in \{200, 190, ..., 10\}$ Hz (without any smoothing). We note from Fig. 2 that the sampling frequencies above 40 Hz are not needed as the performance is approximately constant over this value. This frequency is recommended to be used in the machine learning-based fall detectors as it is the minimal frequency for efficient performance. This result is justified also theoretically as the maximum frequency of human movements is 20 Hz [10]. That is why it is sufficient to acquire data using 40 Hz sampling frequency (Nyquist frequency). We note also from Fig. 2 that the SVM-based proposed method outperforms the reference algorithms in terms of accuracy and specificity over all sampling frequencies whereas it shows approximately the same sensitivity as the SVM-based reference one. Table 1 shows the preliminary numerical results for $F_s = 40$ Hz. As expected, the four machine learning-based methods outperform the threshold-based one. We can note also that the SVM-based proposed method outperforms Mezghani approach [9] in terms of all performance criteria with a significant difference in the specificity, meaning that a lower rate of false alarm could be achieved using our method thanks to the efficient extracted features. Table 2 shows the average execution time of the considered methods. The execution time is comparable for the four machine learning-based methods. Now, if the threshold-based algorithm shows a reduced execution time, it is at the expense of performance quality.

Table 1. Comparison study in terms of accuracy, specificity and sensitivity; $F_s = 40$Hz

Method	Specificity (%)	Sensitivity (%)	Accuracy (%)
Proposed (KNN-based)	97.89	97.06	97.54
Proposed (MLP-based)	99.62	98.26	99.05
Proposed (SVM-based)	97.70	99.73	98.55
Mezghani [9] (SVM-based)	94.44	99.60	96.60
Abdelhedi [8] (Threshold-based)	82.85	54.14	70.87

Table 2. Comparison study in terms of average execution time for $F_s = 40$ Hz

Method	Proposed			Mezghani [9]	Abdelhedi [8]
	KNN-based	MLP-based	SVM-based		
Av. exe. time (ms)	0.6818	0.7240	0.6567	0.6278	0.0254

4   Conclusion

In this paper, an efficient design of a machine learning-based elderly fall detector is proposed. The design takes into account the power consumption issue that is critical in wearable devices. To this end, a single 3-axial accelerometer is used to capture the elderly motion with a sampling frequency of 40 Hz that showed the best trade-off between performance and power consumption. The preliminary results of the proposed system are quite promising. Thanks to the efficient extracted features and the new training procedure, the proposed method outperforms reference algorithms in terms of both sensitivity and specificity throughout the whole range of studied sampling frequencies. The proposed design is under hardware implementation and the performance on hardware will be explored in a future work. In addition, more efficient features would be investigated in order to further reduce the false alarm rate.

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