CareFall: Automatic Fall Detection through Wearable Devices and AI Methods

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Abstract
The aging population has led to a growing number of falls in our society, affecting global public health worldwide. This paper presents CareFall, an automatic Fall Detection System (FDS) based on wearable devices and Artificial Intelligence (AI) methods. CareFall considers the accelerometer and gyroscope time signals extracted from a smartwatch. Two different approaches are used for feature extraction and classification: *i)* threshold-based, and *ii)* machine learning-based. Experimental results on two public databases show that the machine learning-based approach, which combines accelerometer and gyroscope information, outperforms the threshold-based approach in terms of accuracy, sensitivity, and specificity. This research contributes to the design of smart and user-friendly solutions to mitigate the negative consequences of falls among older people.

Keywords
fall detection system, accelerometers, classification algorithms, machine learning, wearable sensors

1. Introduction

Population aging is increasing worldwide. The World Health Organization considers falls among the elderly to be a major global public health challenge [1]. In fact, falls can adversely affect the quality of life in older people, causing them serious physical, psychological, and social consequences, such as contusions, fractures, trauma, motor and neurological damage, or even death [2, 3, 4]. For this reason, it is crucial the design and deployment of user-friendly technologies to detect falls.

In recent years, solutions such as the Personal Emergency Response System (PERS) have been proposed [5]. PERS is a manual system whereby a person, after falling to the ground, must press a warning button (usually in a pendant or bracelet), and an emergency team is immediately dispatched to provide assistance. However, this system might not be a good solution in some

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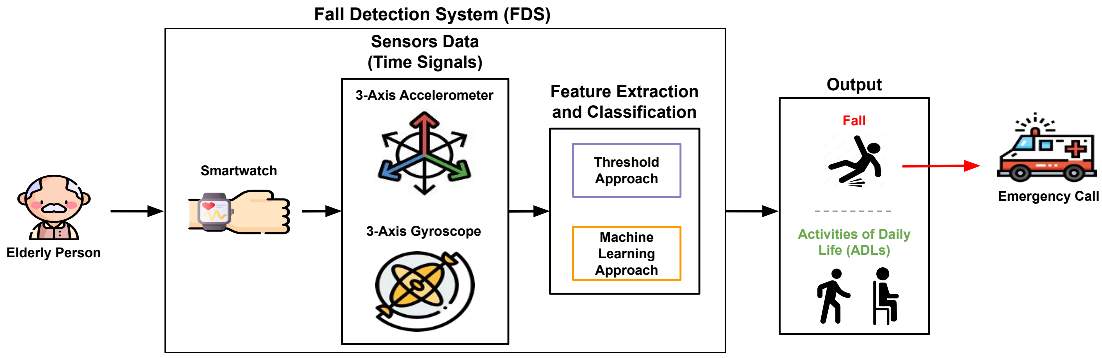

Figure 1: Representation of CareFall, an automatic Fall Detection System (FDS) based on wearable devices and AI methods.

cases, e.g., if the person has fainted or lost consciousness due to the fall and can not press the emergency button.

To overcome the limitations of PERS, a wide variety of Fall Detection Systems (FDS) have been proposed in the last decade, providing automatic and user-friendly solutions for elderly people [3, 6]. Most FDS are based on wearable devices [7], such as belts or bracelets with accelerometer sensors [8, 9, 10], image-based devices, such as indoor surveillance cameras [11, 12], or smartphones [13, 14, 15], among many others.

This paper presents CareFall, an automatic FDS based on wearable devices and Artificial Intelligence (AI) methods. Fig. 1 provides a graphical representation of CareFall. CareFall considers a scenario where the smartwatch is positioned on the wrist, acquiring information related to its inertial sensors, such as the 3-axis accelerometer and gyroscope [16, 17], or heart rate monitor [18, 19]. Once the information is acquired by the smartwatch, the time signals (accelerometer and gyroscope signals) are used for feature extraction and classification. Two different approaches are considered: *i)* threshold-based, and *ii)* machine learning-based. In case the FDS detects a fall, it automatically warns the emergency services.

2. Methods

CareFall considers two of the most popular methods for fall detection in the literature [20]. They are fed to the 3-axis time signals of accelerometer and gyroscope sensors. The sampling frequency of the smartwatch is between 20-25Hz. For a simple and real-time analysis, we consider separate time windows of 1 minute.

1. **Threshold-based**: it is one of the simplest and least computationally expensive solutions to detect a fall. It is based on the extraction of additional time signals from the original accelerometer and gyroscope ones such as the Signal Magnitude Vector (SMV), the Fall Index (FI), and the Absolute Vertical Direction (AVD), among others [21, 22]. After that, a specific threshold is defined for each time sequence. In case the instant value of the time sequence surpasses the threshold, the output of the system would be fall. It is important to highlight that, in case of considering several time signals in the analysis (e.g., SMV, FI,

and AVD), the final output of the system would be based on the majority voting of all the time signals considered.

2. **Machine Learning-based**: this approach automatically learns the discriminative patterns for the task using data. From the original 6 time signals (3-axis accelerometer and gyroscope) and 2 additional time signals (SMV of the accelerometer and gyroscope), we extract the following 11 global features per time window (1 minute) related to statistical information: Mean, Variance, Median, Delta, Standard Deviation, Maximum Value, Minimum Value, 25th Percentile, 75th Percentile, Power Spectral Density (PSD), and Power Spectral Entropy (PSE). In total, we obtain a feature vector with 44 global features related to the accelerometer information and 44 global features related to the gyroscope.
   Once we have the feature vector with the 88 global features, we train machine learning classifiers for the task of fall detection. The most widely used algorithms are K-Nearest Neighbor (KNN) [23], Support Vector Machine (SVM) [24], Gradient Boosting (GB) [25], Random Forest (RF) [25], and Artificial Neural Network (ANN) [26], among others.

3. Experimental Setup

Two popular public databases are considered in the experimental framework of the paper: Erciyes Univesity [23] and UMAFall [27]. Table 1 shows the most relevant information from these databases: *i)* the number of Activities of Daily Life (ADLs) such as walking, sitting, lying down, etc., and simulated falls (forward, backward, sideways, etc.); *ii)* participant information (number, gender, height, weight, and age range); *iii)* type of time signals captured (accelerometer and gyroscope); *iv)* sensor position; and *v)* the sampling rate. The main criteria for selecting these databases were the position of the sensor (wrist), the sampling rate of the sensors (20-25Hz), and the variability in the type of activities and falls.

Regarding the experimental protocol, both databases are divided into development (80% of participants) and final evaluation (20% remaining participants) datasets. As a result, different subjects are considered for the training and final evaluation of CareFall. Regarding metrics, we consider three popular metrics in the literature: Sensitivity (SE), Specificity (SP), and Accuracy. SE refers to the probability of detecting a fall, SP to the probability of detecting a non-fall (i.e., ADLs), and accuracy to the overall system performance.

Table 1
Selected public databases to train and evaluate CareFall.

Database (Year) [Ref.]	# Participants (Females/Males)	Participant Information	# Tasks (ADLs/Falls)	# Samples (ADLS/Falls)	# Sensor Position	Captured Signals	# Sampling Rate (Hz)
Erciyes University (2014) [23]	17 (7/10)	Age: 19-27 years Height: 157-184 cm Weight: 47-92 kg	36 (16/20)	3060 (1360/1700)	Wrist (right)	Acc: 3-axis Gyr: 3-axis	25
UMAFall (2016) [27]	17 (7/10)	Age: 18-55 years Height: 155-195 cm Weight: 50-93 kg	11 (8/3)	531 (322/209)	Wrist (left)	Acc: 3-axis Gyr: 3-axis	20

4. Experimental Results

Table 2 (top) shows the results for the Erciyes University database over the final evaluation set. The results presented correspond to the best configuration of each fall detection approach. The results obtained in general (accuracy) with the threshold-based approach are significantly worse compared with the machine learning approach (77.3% vs. 98.4%), resulting in a higher number of false positives (no falls detected as falls). This trend can be observed by looking at the specificity (68.4% vs. 96.7%). Nevertheless, it is interesting to remark that the Threshold approach outperforms the Machine Learning approach in terms of sensitivity (100% vs. 98.9%), showing to be a simple but efficient approach to detecting falls. In addition, analysing the Machine Learning approach, we can see how the combination of accelerometer information (44 global features) and gyroscope information (44 global features) achieves the best results.

Finally, we can also see in Table 2 (bottom) the results achieved for the public UMAFall database. Similar conclusions are obtained, although better results are achieved on Erciyes database. This can be produced due to the quality of the device and the acquisition process. This seems to indicate that combining accelerometer and gyroscope information is a good practice for the fall detection task.

Table 2
Results obtained in terms of accuracy, sensitivity, and specificity for Erciyes University and UMAFall databases over the final evaluation set. Results from both Threshold- and Machine Learning-based approaches are included.

Erciyes University (2014) [23]	Threshold Approach (SMV)	Machine Learning Approach (RF)		
		Accelerometer (44 Features)	Gyroscope (44 Features)	Acc + Gyr (88 Features)
Accuracy	77.3%	97.2%	95.3%	98.4%
Sensitivity (SE)	100.0%	98.5%	97.9%	98.9%
Specificity (SP)	68.4%	95.8%	91.9%	96.7%

UMAFall (2016) [27]	Threshold Approach (FI)	Machine Learning Approach (SVM)		
		Accelerometer (44 Features)	Gyroscope (44 Features)	Acc + Gyr (88 Features)
Accuracy	75.8%	93.9%	93.2%	95.5%
Sensitivity (SE)	100.0%	100.0%	97.3%	98.6%
Specificity (SP)	66.3%	91.6%	91.6%	93.7%

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