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Advanced Solutions Aimed at the Monitoring of Falls and Human Activities for the Elderly Population

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Received: 28 February 2019; Accepted: 13 August 2019; Published: 20 August 2019

Abstract: Ageing is a global phenomenon which is pushing the scientific community forward the development of innovative solutions in the context of Active and Assisted Living (AAL). Among functionality to be implemented, a major role is covered by falls and human activities monitoring. In this paper, main technological solutions to cope with the aforementioned needs are briefly introduced. A specific focus is given on solutions for Falls recognition and classification. A case of study is presented, where a classification methodology based on an event-driven correlation paradigm and an advanced threshold-based classifier is addressed. The receiver operating characteristic (ROC) theory is used to properly define thresholds' values while, in order to properly assess performances of the classification methodology proposed, dedicated metrics are suggested, such as sensitivity and specificity. The solution proposed shows an average Sensitivity of 0.97 and an average Specificity of 0.99.

Keywords: human activity; falls; measurement methodology; fall detection; classification strategy; threshold algorithm; advanced threshold algorithm

1. Introduction

Falls represent a serious issue which can have catastrophic consequences and the need for ICT (Information and Communication Technologies) based solutions is hence emerging to improve the life quality and autonomy of frail people, with particular regards to falls' detection and classification.

In the last decades, the interest of the scientific community in the field of assistive technology is acquiring more and more visibility, especially due to the phenomenon of population ageing.

Just to mention few examples, in United Kingdom in 1997 around one in every six people (15.9%) were aged 65 years and over, increasing to one in every five people (18.2%) in 2017 and is projected to reach around one in every four people (24%) by 2037 [1]. In 2018 the Italian resident population amounted to about 60 million units. The average age is 45.2 years, reflecting a structure by age where only 13.4% of the population is under 15, 64.1% between 15 and 64 and 22.6% is 65 and older [2].

Most countries will see the number of elderly (60+) doubled in the coming 30 years, but also the number of the oldest-old (80+) will grow drastically in the long run. Specifically, considering the European country, the share of the elderly in the total population is expected to increase from 21% now to around 34% in 2050. In absolute terms, 37 million people are expected to be aged 80 and over in 2050, an increase by almost 160% compared with 1995 [3].

From the aforementioned statistics, it is straightforward to deduce the need for solutions assuring an improved quality of life and independence of the elderly.

To address this issue, in the past few years a significant research activity, focusing on advanced and reliable solutions to monitor frail people, has been developed [4–14]. These systems would directly benefit elderly people, by providing them with more autonomy, reducing the need for moving to institutionalized care center, enabling timely and effective intervention in case of need, and ultimately reducing the emotional and financial burden for the elderly and their families. The use of technology would also reduce the overall costs of health and social care [15].

Valid monitoring systems can be extremely beneficial in analyzing deviations with respect to the normal behaviour of an individual which can be strategic for early detection and treatment of worsening health conditions [16].

Celler et al. [17], during a studies of behavioural monitoring, discovered that the health condition of a subject can be estimated by check a set of simple parameters such as the mobility, sleep patterns, washing and toilet facilities, that have been demonstrated to be representative of the interaction of the subject with his environment. Commonly analyzed human activities are actions typically performed during the day, such as dressing, standing, sitting, walking, climbing stairs and laying down. Many different technologies have been proposed in the literature for human activities and falls monitoring. These include wearable multi-sensor architectures, developed by customized solutions, smartphones, or a combination of these systems.

The main aim of this paper is to present an overview of different approaches for falls detection, with a specific focus on methodologies developed at the SensorLab of the University of Catania, Italy, for fall classification. Robustness of developed methodologies against other user behaviors, such as sitting, is also demonstrated. A detailed discussion and more experimental results related to the classification paradigms developed can be found in journal papers already published by the authors [18,19].

2. Falls and Human Activities Detection Techniques: A Brief Overview

Following the classification provided in [20], falls and human activities detectors can be classified as wearables, non-wearables (ambient sensors, vision sensors, and radio-frequency sensors), and hybrid systems.

2.1. Wearable Solutions

Different approaches have been proposed for falls and human activities detection in the Active Assisted Living contexts using wearable solutions. Two main categories are addressed by the current State-of-the-art: customized devices [21–24] and smartphone-based platforms [25–29].

2.1.1. Customized Systems

Inertial solutions have been widely investigated by researchers and scientist as a practical and unobtrusive way to monitor people activities, while preserving subject's privacy. Such systems show good performances in detecting and classifying falls, human activities and physiological parameters. Focusing on falls detection systems, in the following some examples are presented.

In [21] the authors present and discuss a computationally low-demanding algorithm for fall detection. The system utilize a triaxial accelerometer and a supervised clustering approach, implemented through one-class support vector machine classifier. Results clearly shows that the approach has been proved to be invariant to age, weight, height of people, and to the relative positioning area of the measurement system thus allowing to overpower typical drawbacks arising from threshold-based methodologies such as the need to adjust of a number of parameters depending on the user's specifications.

In [5] a multisensor data fusion approach is investigated for the sake of falls and human activities classification with particular regards on elders and people with neurological pathologies. The working principle of the solution consist on an advanced signal processing technique carried out on data provided by an accelerometer and a gyroscope. Specifically, the system under study can recognize critical events such as falls or prolonged inactivity, to monitor the user posture, and to notify alerts to caregivers. A major outcome of this work relies on the information provided by the system, which can be useful to monitor the evolution of the user pathology with particular interest in rehabilitation tasks. The mean value of the sensitivity index computed across different classes of falls and human activities considered through the paper is 0.81%, while the average value of the specificity index is 0.98%.

In [30] a system based on a detection strategy consisting on an automatically adjustable threshold value for a pre-impact fall detection system is presented. Several experiments have been conducted evaluating performance such as sensitivity, specificity and accuracy. The results of proposed method can detect the pre-impact fall from normal activities of daily living with 99.48% sensitivity, 95.31% specificity and 97.40% accuracy with 365.12 msec of lead time.

A fall detection system, based on an instrumented insole is presented in [31]. Since high-acceleration activities have a high risk for falls, and because of the potential damage that is associated with falls during these activities, four low-acceleration activities, four high-acceleration activities, and eight types of high-acceleration falls have been investigated. A Support Vector Machine model's Leave-One-Out cross-validation provides a fall detection sensitivity (99.6%), specificity (100%), and accuracy (99.9%). The classification results are comparable to other fall detection models in the State-of-the-art, while also including high-acceleration ADLs to challenge the classification model.

In [32], the authors propose a fall detection methodology based on a non-linear classification feature and a Kalman filter with a periodicity detector to reduce the false positive rate. The methodology requires a sampling rate of only 25 Hz; it does not require large computations or memory and it is robust among devices. The system has been tested using the SisFall dataset achieving 99.4% of accuracy.

Wang et al., in [33], present a fall classification methodology based on two new inertial parameters: acceleration cubic-product-root magnitude (ACM) and angular velocity cubic-product-root magnitude (AVCM). These indexes have been introduced to improve the selectivity of threshold-based fall detection methods, and evaluate strategies to distinguish falls from other activities of daily life (ADLs). Inertial data on four types of simulated falls and eight types of ADLs were collected. Two public datasets, UMAFall and Cognent Labs, were also included to evaluate fall detection methods. Results show that a hybrid use of ACM and AVCM parameters allows to reduce the misclassification rate compared to single-parameter methods.

2.1.2. Smartphone-Based Solutions

Although different surveys seem to reveal that smartphone-based assistive devices are not fully accepted by elderly, due to apparent request of technological skills, it must be considered that the monitoring of falls and human activities do not require any action by the user, thus habilitating fully smartphone-based solutions as a convenient way to perform such tasks [34].

In [18] authors present a smartphone-based strategy for fall detection. The developed methodology uses an event-driven approach to generate features to be successively processed by a threshold classification paradigm.

This solution, compared to systems using only the final posture to recognize fall, which are subjected to fail in case of extra movement of the user after the fall, analyzes the inertial signal evolution recorded during the fall event, which makes the system robust against exogenous user behaviours.

A fall detection system, developed on smartphones exploiting a two-step algorithm to monitor and detect fall events using the embedded accelerometer signals, is presented in [35]. The proposed solution uses techniques to properly detect fall-like events (such as lying on a bed or sudden stop after running) based on a multiple kernel learning support vector machine along with a threshold based strategy. Experimental results reveal that the system detects falls with high accuracy (97.8% and 91.7%), sensitivity (99.5% and 95.8%), and specificity (95.2% and 88.0%) when placed around the waist and thigh, respectively. The system also achieves a false alarm rate of 1 alarm per 59 hours of usage.

In [36] the authors propose a fall detection algorithm made up of a feature extraction and recognition processing. Six features were analyzed where, four of them, were related to the gravity vector extracted from accelerometer data. During the testing phase, a set of six features was clustered by support vector machine. The main feature contains the vertical directional information and provides a distinct pattern of fall-related activity. This feature acts as a trigger-key in recognition processing to avoid false alarms which lead to excessive computation. The results show that the algorithm could achieve a sensitivity of 96.67% and specificity of 95%.

Another interesting work is the one discussed in [37]. The paper proposes a fall classification strategy consisting on different approaches (detection of inactivity, detection of falls by thresholds analysis, detection of falls by device orientation analysis and detection of falls with decision trees algorithm) merged together, in order, to improve the efficiency and accuracy of the fall detection process. Through the databases Mobifall, Mobifall2 and a database developed by this study, tests performed with the proposed methodology showed 87.65% of specificity and 95.45% of sensitivity, with maximum detection delay of 3 seconds.

In [38], an automated fall detection system based on smartphone audio features is developed. The spectrogram, mel frequency cepstral coefficents (MFCCs), linear predictive coding (LPC), and matching pursuit (MP) features of different fall and no-fall sound events are extracted from experimental data. Based on the extracted audio features, four different machine learning classifiers: k-nearest neighbor classifier (k-NN), support vector machine (SVM), least squares method (LSM), and artificial neural network (ANN) are investigated for the sake of fall and no-fall events classification. Sensitivity, specificity, accuracy, and computational complexity have been evaluated for each audio feature. The best performance is achieved using spectrogram features with ANN classifier with sensitivity, specificity, and accuracy all above 98%.

Another work investigating the use of the inertial sensing feature of a smartphone for human falls detection is presented in [28] along with an application for the administration of a popular and standardized test in the field of human mobility assessment.

The fall detection methodology illustrated in [29] is based on the exploitation of acceleration and orientation information gathered by smartphone sensors and processed by threshold algorithms.

2.1.3. Non-Wearable Solutions

Digging into the State-of-the-art, it appears evident the supremacy of the camera-based falls and human activities detection systems in case of non-wearable solutions. A reason relies on the fact that, nowadays, cameras are becoming increasingly common among consumers. Cameras can be employed in many different contexts, such as the active assisted living one and for personal security. A major advantage of these systems rely on their capability to monitor more complex behaviours as respect to wearable solutions.

Although analyzing visual streams from cameras to automatically detect users' behaviour is a challenging task [39], since it implies the need to differentiate users from environment where the users operates, human activities and falls analysis has anyway attracted considerable attention in the computer vision and image processing communities [40–43].

As an example, in [40], Messing et al. have used a particular technique for daily activity recognition, based on the velocity histories of tracked key points. The solution exploits a generative mixture model for video sequences, which shows similar performance compared to local spatio-temporal features on the KTH activity recognition dataset (a dataset provide by KTH Royal Institute of Technology in Stockholm).

In [41] the authors discuss a solution based on the use of an RGB-D (Kinect-style) cameras for fine-grained recognition of kitchen activities. The developed system combines depth (shape) and colour (appearance) to solve a number of perception problems fundamental for smart space applications: locating hands, identifying objects and their functionalities, recognizing actions and tracking object state changes through actions. The system is able to robustly track and recognize steps really detailed through cooking activities.

A key challenge in the computer vision context deals with the detection and classification of falls based on variations in human silhouette shape. In order to face this problem, the study presented in [44] proposes a multivariate exponentially weighted moving average (MEWMA) monitoring scheme, which is effective in detecting falls because it is sensitive to small changes. In order to distinguish real falls from some fall-like gestures, a classification stage based on a support vector machine (SVM) is applied on detected sequences. The methodology has been validated using the University of Rzeszow fall detection dataset (URFD) and the fall detection dataset (FDD). The results of the MEWMA-based SVM are compared with three other classifiers: neural network (NN), naïve Bayes and K-nearest neighbour (KNN). Results show the capability of the developed strategy to distinguish fall events.

In [45] a vision-based solution using Convolutional Neural Networks to detect falls in a sequence of frames is proposed. To model the video motion, and to make the system independent on the considered scenario, an optical flow images as input to the networks followed by a novel three-step training phase is introduced. The method has been evaluated in three public datasets achieving state-of-the-art results.

2.1.4. Hybrid System

In many application scenarios, there is a need to clearly differentiate activities characterized by similar motions or gesture but corresponding to different behaviours. Typically, these situations can arise from actions like carrying a glass of water or carrying a pillbox, or when an object is used or simply carried around.

A solution for the aforementioned problems is discussed in [46], where an approach based on direct motion measurements with inertial sensors and detection of object interaction with RF-ID for high-level activity recognition is proposed. The system uses a sensor fusion strategy based on different levels of abstraction for simultaneously integrating many channels of heterogeneous sensor data. This approach was evaluated with one Activity of Daily Living (ADL) breakfast scenario and one home care scenario where the proposed approach reached accuracy of 97% and 85% respectively.

A paper discussing the performance limitations of using individual wearable sensors instead of hybrid solutions, especially for the classification of similar activities, is presented in [6]. The is mainly based on a data fusion strategy of features extracted from experimental data collected by different sensors: a tri-axial accelerometer, a micro-Doppler radar, and a depth camera. Preliminary results show that combining information from heterogeneous sensors improves the overall performance of the system. The classification accuracy attained by means of this fusion approach improves by 11.2% compared to radar-only use, and by 16.9% compared to the accelerometer. Furthermore, adding features extracted from an RGB-D Kinect sensor, the overall classification accuracy increases up to 91.3%.

The time synchronization issue, when dealing with data fusion based on samples from several systems, is discussed in [47]. This work presents a technical platform for the efficient and accurate synchronization of the data captured from RGB-Depth cameras and wearable inertial sensors, that can be integrated into AAL solutions.

2.1.5. Conclusive Remarks

The solutions briefly cited in this section highlight the huge number of alternatives to detect falls and other human activities. The choice of the right technology is usually driven by the specific application, with particular regards to performances requested (classification accuracy, sensitivity and specificity), user skills, computational power requirements, the need for structured environment (e.g., camera-based solutions). Wearable solutions based on inertial sensors have been proved to represent the right compromise between reliability and ease of use. In general, it must be reminded that a reliable fall detector must exhibit properties such as robustness against users' characteristics (e.g., height, weight), robustness against exogenous behaviour and suitable classification specificity (e.g., a fall is detected and classified in the right fall category). A case study developed by the research group working on Assistive Technology at the SensorLab of the University of Catania is presented in Section 3. The proposed solution is a wearable device which exploits an event-driven paradigm to guarantee suitable classification performances.

3. Event Driven Methodologies for Fall Detection and Classification

The wearable solution presented through this section exploits an event-driven approach which is able to guarantee high sensitivity and specificity of the classification task. Moreover, in order to improve the system robustness against users' characteristics signals provided by the sensing platform are processed by a normalization routine.

3.1. The Event-Driven Classification Methodology

The classification methodology, schematized in Figure 1, is based on an event-driven correlation paradigm, which is known to be one of the most powerful, yet computationally manageable, methods of classification for the invariance to the translations and the robustness to the additive noise of the signal. The paradigm aims to extract robust features from the unknown target event to be classified. Adopted features consist in the correlation (named XCOR in Figure 1) operated between events signatures and the unknown pattern (run-time acquired data from a 3-axis accelerometer), which has been suitably pre-processed by a normalization routine.

Such features are then processed by a threshold-based classifier in order to estimate the class to which the event belongs. The Receiver Operating Characteristic (ROC) theory is used to properly define the thresholds' values.

Moreover, in order to improve the classification performances of the system, the paradigm is reinforced by integrating the post-fall evaluation of the accelerometer axes, when specific conditions occur (details are provided in Section 3.1.3).

It must be specified that both signatures and thresholds identification are totally handled offline by means of a Matlab script. Those phases do not require to be executed each time the system perform a classification but, once determined, they are not subjected to changes. The classification strategy uses both the signatures and the thresholds as known data. On the contrary, both the correlation and classification phase are meant to be executed online [19].

This classification strategy has been specifically thought for its implementation in a real power-limited embedded system where, more complicate classification approaches, such as the ones based on machine learning techniques, can be hardly implemented. Although its implementation is not the focus of this paper, a previous work [19], which has laid the basis for this, shows a first implementation in an embedded system.

With the aim to assess performances of the classification methodology, dedicated metrics, such as Sensitivity and Specificity (see Section 5), have been used.

A major advantage of the classification paradigm adopted relies on its low computational demand and adaptability to several different application contexts.

In the following main elements of the classification methodology are addressed.

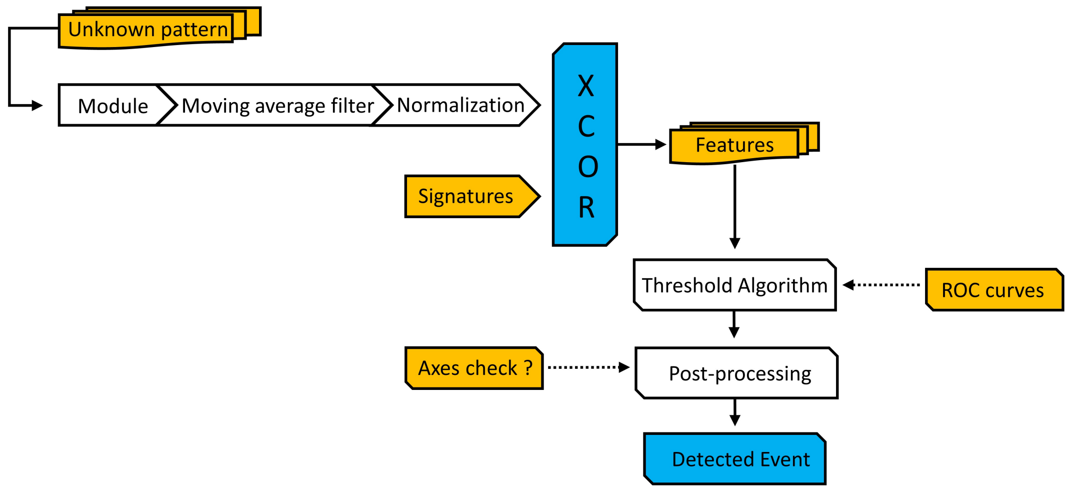

Figure 1. Paradigm adopted for the sake of events classification.

3.1.1. Signature: Definition and Building Process

A signature is defined as a typical time evolution of the acceleration magnitude uniquely describing a specific event. In order to build a reliable set of signatures (one per each class of events), a high-quality dataset, including several observations for each class of falls and human activities, is mandatory, as the one presented in Section 4 [19]. For each set of events belonging to the same class, the following pre-processing steps have been carried out:

- Module computation, whose equation is shown in (1).

$$M(i) = \sqrt{x(i)^2 + y(i)^2 + z(i)^2} \quad \text{for} \quad i = 1, 2...., n \tag{1}$$

  with n number of samples of the acquired signal.
- Low pass filtering by means of a moving average, whose equation is shown in (2).

$$M_a(i) = \frac{1}{k} \sum_{j=-a_1}^{a_2} M(i+j) \quad \text{for} \quad i = a_1, 2...., n - a_2 \tag{2}$$

  with:

  - n = number of samples of the acquired signal
  - a_1 = number of samples previous to i
  - a_2 = number of samples subsequent to i
  - $k = a_1 + a_2 + 1$
- Normalization, whose algorithm (Algorithm 1) is shown below.

Algorithm 1: Normalization algorithm

Result: Provides the normalized values, $N_{M_{a_{x_i}}}$, of the filtered vectors $M_{a_{x_i}}$

Input: The class of event $E = \{M_{a_{x_1}}, M_{a_{x_2}}, ...M_{a_{x_n}}\}$ with n number of acquisitions

for *each vector* $M_{a_{x_i}} \in E$ **do**

  $m(i) = max(M_{a_{x_i}})$

end

$Max = max(m_1, m_2, ...m_n)$

for *each vector* $M_{a_{x_i}} \in E$ **do**

  $N_{M_{a_{x_i}}} = \frac{M_{a_{x_i}}}{Max}$

end

- Alignment. The alignment algorithm is based on the time delay between patterns, estimated by computing the cross-correlation between signals. First the cross-correlation has been computed according the following Equation (3):

$$\hat{R}_{xy}(r \cdot \Delta T) = \begin{cases} \sum_{n=0}^{N-r-1} x_{n+r} \cdot y_n & \Delta T \geq 0 \\ \hat{R}_{xy}(-r \cdot \Delta T) & \Delta T < 0 \end{cases} \quad (3)$$

with

  - n = number of acquired samples
  - x_n = signature
  - y_n = filtered and normalized acceleration module
  - r = sample number
  - ΔT = sampling time

consequently, the time instant where the biggest value of $\hat{R}_{xy}$ is found, has been used to shift one signal in order to align them. The algorithm compute the correlation within a time windows of 300 ms.

- Averaging the aligned vectors.

Examples of signatures for the classes of events considered in the case study presented in Section 4 are shown in Figure 2.

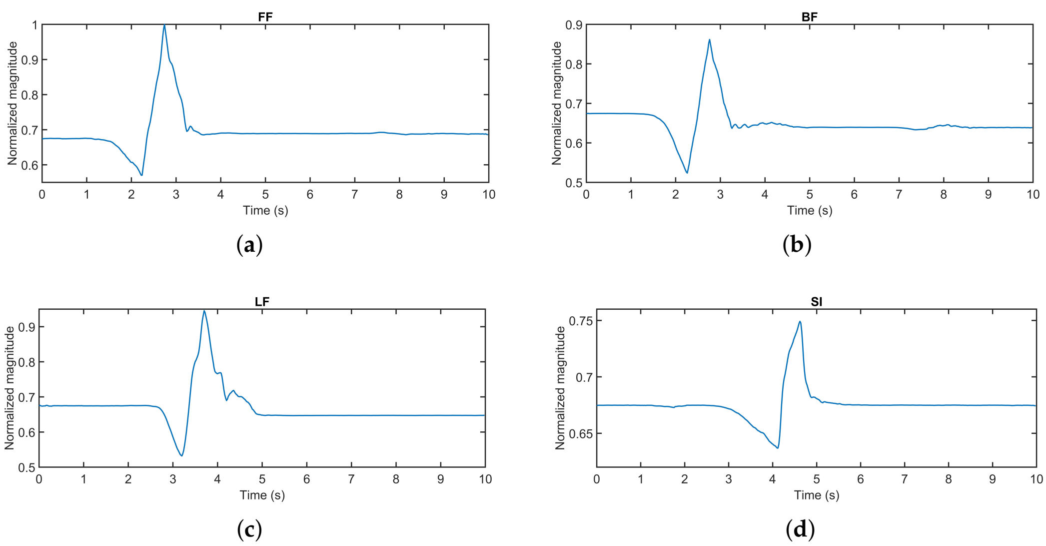

Figure 2. The generated signatures. (**a**) Forward Fall; (**b**) Backward Fall; (**c**) Lateral Fall; (**d**) Sitting.

3.1.2. Pre-Processing of An Unknown Pattern and Features Generation

Initially, a new acquired and unknown pattern, is pre-processed by following steps indicated in Figure 3.

With the aim to make the classification procedure users' independent, a data normalization has been computed both for the signatures and the inertial quantities representing the unknown pattern; this procedure makes the solution robust against users' characteristics, such as weight and height. The normalization procedure constrains signals in the range [−1,1], thus preserving the signal's dynamics, while assuring the generalization of the classification strategy. This approach also increases the robustness of the system against small variations of the device position on the user body, as well as it reduces the need for a tuning phase.

Once both the signatures and the unknown patterns have been properly processed, the cross-correlations between the acceleration module of the unknown event and the set of signatures representative of all the candidate class of events (falls and other human activities) have to be computed. The maximum values of such cross-correlations represent features to be processed by the classification paradigm.

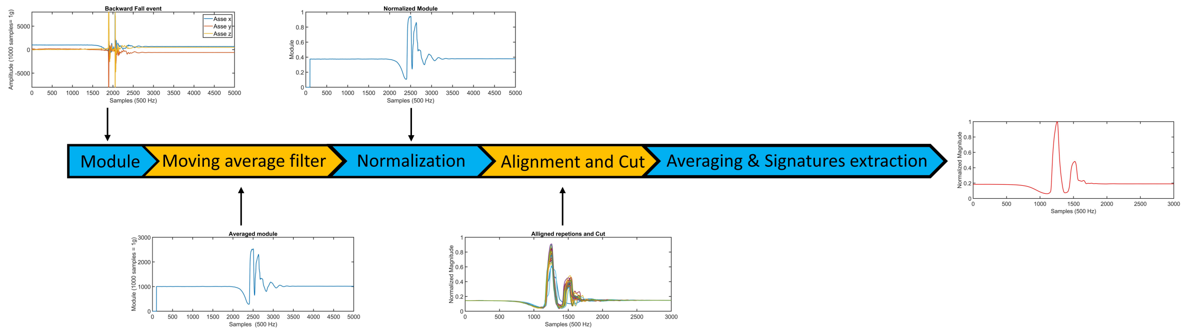

Figure 3. The procedure adopted for the signature generation. The example shows the steps for the forward fall event.

3.1.3. Classification Procedure

The threshold based classification algorithm (abbreviated as TA) compares the extracted features with threshold values, to define the potential class or classes to which the unknown target belongs. A pattern is classified as belonging to a specific class if the maximum value of its cross-correlation with the corresponding signature (feature) overpasses a predefined threshold.

As already stated, the ROC theory has been used to define optimal thresholds values for each class of the considered events. The ROC curve theory provides theoretical support to the classification problem where a classifier is required to map each instance to one of two classes [48]. The general strategy adopted by the ROC theory allows to identify thresholds which maximize both the sensitivity and specificity of the classification methodology. In order to guarantee this specification, the intersection between the specificity and sensitivity curves has been adopted as the selection criteria for thresholds identification [18]. It must be observed that the result of the classification strategy above described can lead to multiple classifications (an unknown pattern could be recognized as belonging to different classes) and unclassified events (an unknown pattern could be classified as not belonging to any of the considered classes of events). In order to overcome such mis-classifications a post-processing elaboration (Advanced Threshold Algorithm—ATA) has been also implemented. To such aim, two terms have to be defined: (1) fall dynamics evaluation and (2) post-fall evaluation; the word "dynamic" is related to the nature of the investigation which takes into account the time evolution of the event to be classified, while the post-fall evaluation takes into account the orientation of the accelerometer axes at the end of the dynamic evolution of the unknown event. The ATA represents an improvement as respect to the TA version since it adds the post-fall evaluation of the acceleration axes. It is used only in case of an unclassified event or multiple classifications. In the first scenario, the classification result totally relies on the post-fall classification. In case of multiple classifications, the post-fall evaluation is used to select the most likely classes among those identified by the TA algorithm. Actually, the matching between the post-fall evaluation and the multiple classifications will define the class to which the unknown event belongs.

4. A Case of Study

The classes of events, E, considered through this paper are:

1. Backward falls (FB) (50 repetitions);
2. Forward falls (FF) (50 repetitions);
3. Lateral falls (LF) (50 repetitions);
4. Sitting events (SI) (50 repetitions).

Each event has been acquired for 10 s, with a sampling frequency, f_s, of 500 Hz. Although a sampling rate of 100 Hz has been demonstrated to be suitable in case of Fall detector, since the aim of this work is the classification of different kind of Falls, a higher sampling rate has been used to avoid any loss of information provided by the accelerometer signals. The acquisition were performed using ultralow-power/high-performance/three-axis nanoac- celerometer, ST LIS3DH. The accelerometer has dynamically capable of measuring accelerations with output data rates user selectable full scales of $\pm$2g/$\pm$4g/$\pm$8g/$\pm$16g and it is ranging from 1 Hz to 5 kHz. It provides a 16-bit information by an Inter Integrated Circuit/Serial Peripheral Interface digital output interface. The sensor has been positioned on the user's right hip since this is close to the center of the body mass. The inertial monitoring of such body point will provide reliable information on the body movements, which are minimally affected by sudden limb motion artifacts.

In particular, 10 users, with different stature and weights and ranging between 25 and 44 years old, with a mean of 37 years and a standard deviation of 5.56 years, have been selected to simulate both falls and sitting events, 5 times each. Characteristics of users involved in the experimental trials are summarized in Table 1.

Table 1. Characteristics of the users involved in the test.

	User	**User**	**User**	**User**	**User**	**User**	**User**	**User**	**User**	**User**
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Gender	Male	Male	Female	Male	Male	Female	Male	Male	Female	Male
Age [year]	36	25	40	36	31	44	40	36	39	42
Height [m]	1.75	1.85	1.62	1.78	1.66	1.54	1.81	1.65	1.58	1.92
Weight [Kg]	90	82	54	85	72	52	81	63	60	105

It is mandatory to underline that the aim of this case study is not to distinguish falls from the sitting event but rather to classify different kinds of falls (forward fall and backward fall as an example). However, the sitting event has been included in order to the test the robustness of the methodology proposed against a non-fall event which shows a fall-similar dynamic.

It is mandatory to clarify that this work reports on laboratory tests performed by people belonging to the Research Team with different heights, ages and weights in safe conditions (falls have been simulated using a mattress as a common practice adopted also by other research groups). Each participant was requested to sign an informed consensus regarding the purpose of the study and working conditions. Nevertheless, every precaution was taken to ensure user safety during experiments. Moreover, it must be considered that the Device Under Test is not belonging to the class of medical devices, being an external inertial unit used to monitor the dynamic of the user body.

Although users addressed by the solution should be frail people, the choice of using healthy subjects performing tests in safe conditions, has been taken to avoid injuries during this preliminary phase. To support this choice, it must be stressed out that the event-driven cross-correlation classification strategy developed is robust against light modifications of signal dynamics, thus confirming that the classification procedure can be successfully extended to a new data set generated by real users.

In particular, 40 of the 50 acquisitions have been used to generate the event-related signature while, the remaining 10, have been used for test purposes. The reason behind the larger number of data used for signatures generation is due to the need of generating typical time evolution of the acceleration module for each of the considered classes. To such aim, the availability of a dataset able to properly represent the typical dynamics of each class of events is mandatory. Signatures generated using data collected during the experiments are shown in Figure 2.

As an example, features obtained are reported in Table 2. For the sake of clarification, each row of the Table 2a is an FF event taken from the test set. In particular, each element of the row is the correlation result between the FF event and the FF, BF, LF and SI signature. For example, the element in column 2 is the maximum correlation between the FF event and the BF signature.

As it clearly emerges, higher values of the features have been obtained in case of the correlation of the pre-processed unknown pattern with the its related signature: the first column of the Table 2a shows a greater value of the features because it contains the correlation between FF events and the FF signature, while, the last column of the Table 2d, shows a greater value of the features because it reports the correlation between SI events and the SI signature. The same reasoning apply to the other events.

It should be noticed also that high features values can be obtained also in case of cross-correlation between a pattern belonging to a class and the signature of a different class (this is particularly evident between the FF event and the BF one). This scenario, which could bring to mis-classifications, can be justified by similar dynamics of the two class of events.

Table 3 shows the optimal threshold, for each class of events here addressed, evaluated by using the ROC curves theory [5,18].

Each threshold value shown in Table 3, is related to the corresponding column of Table 2, which is the one associated to its signatures. As an example, the threshold value for the SI event (0.88) only applies to the SI column in Table 2a. In the same way the threshold value for the BF event (0.95) only applies to the BF column in Table 2a.

The result of the comparison between feature values and the adopted thresholds will produce 1 in cases the feature value is higher than the corresponding threshold, and 0 in the opposite case. According to the above mentioned procedure, results shown in Table 4 have been obtained; observing this Table, occurrences introduced in Section 3.1.3 can be identified. Considering Table 4a containing results for the FF events, any classification has been performed in the third and sixth rows; considering the table containing the SI events, different multiple classifications can be observed.

These occurrences can be reduced taking into account the post-fall classification, implemented by the ATA paradigm. Results shown in Table 5 demonstrate reduction of mis-classifications.

Table 2. Examples of correlation indexes.

(a) Correlation Indexes for the FF Event				
Repetition	**FF**	**BF**	**LF**	**SI**
1	0.97	0.88	0.87	0.69
2	0.95	0.90	0.87	0.74
3	0.93	0.94	0.89	0.85
4	0.96	0.89	0.88	0.73
5	0.96	0.88	0.87	0.70
6	0.93	0.93	0.88	0.82
7	0.94	0.84	0.84	0.65
8	0.94	0.85	0.85	0.66
9	0.97	0.93	0.89	0.77
10	0.95	0.92	0.86	0.73
(b) Correlation Indexes for the BF Event				
Repetition	**FF**	**BF**	**LF**	**SI**
1	0.82	0.92	0.89	0.81
2	0.85	0.94	0.87	0.83
3	0.90	0.99	0.88	0.81
4	0.87	0.93	0.87	0.84
5	0.92	0.98	0.89	0.87
6	0.91	0.98	0.89	0.87
7	0.93	0.98	0.90	0.87
8	0.90	0.99	0.88	0.81
9	0.88	0.94	0.87	0.82
10	0.84	0.93	0.88	0.82
(c) Correlation Indexes for the LF Event				
Repetition	**FF**	**BF**	**LF**	**SI**
1	0.89	0.88	0.95	0.84
2	0.87	0.89	0.97	0.85
3	0.88	0.89	0.97	0.85
4	0.89	0.89	0.98	0.84
5	0.88	0.91	0.98	0.84
6	0.84	0.89	0.92	0.85
7	0.85	0.89	0.98	0.87
8	0.84	0.90	0.96	0.86
9	0.87	0.91	0.97	0.86
10	0.86	0.91	0.92	0.84
(d) Correlation Indexes for the SI Event				
Repetition	**FF**	**BF**	**LF**	**SI**
1	0.76	0.95	0.84	0.99
2	0.76	0.91	0.83	0.98
3	0.75	0.91	0.85	0.99
4	0.75	0.91	0.85	0.99
5	0.76	0.95	0.84	0.99
6	0.76	0.92	0.85	0.99
7	0.76	0.92	0.86	0.99
8	0.76	0.91	0.83	0.99
9	0.75	0.91	0.83	0.99
10	0.77	0.95	0.84	0.99

Table 3. Threshold values computed by means of the ROC curves.

FF	BF	LF	SI
0.94	0.95	0.93	0.88

Table 4. TA algorithm classification.

(a) FF Events				
Repetition	**FF**	**BF**	**LF**	**SI**
1	1	0	0	0
2	1	0	0	0
3	0	0	0	0
4	1	0	0	0
5	1	0	0	0
6	0	0	0	0
7	1	0	0	0
8	1	0	0	0
9	1	0	0	0
10	1	0	0	0
(b) BF Events				
Repetition	**FF**	**BF**	**LF**	**SI**
1	0	0	0	0
2	0	0	0	0
3	0	1	0	0
4	0	0	0	0
5	0	1	0	0
6	0	1	0	0
7	0	1	0	0
8	0	1	0	0
9	0	0	0	0
10	0	0	0	0
(c) LF Events				
Repetition	**FF**	**BF**	**LF**	**SI**
1	0	0	1	0
2	0	0	1	0
3	0	0	1	0
4	0	0	1	0
5	0	0	1	0
6	0	0	0	0
7	0	0	1	0
8	0	0	1	0
9	0	0	1	0
10	0	0	0	0
(d) SI Events				
Repetition	**FF**	**BF**	**LF**	**SI**
1	0	1	0	1
2	0	0	0	1
3	0	0	0	1
4	0	0	0	1
5	0	1	0	1
6	0	0	0	1
7	0	0	0	1
8	0	0	0	1
9	0	0	0	1
10	0	1	0	1

Table 5. Examples of classification performance for the ATA algorithm.

(a) FF Events

Repetition	FF	BF	LF	SI
1	1	0	0	0
2	1	0	0	0
3	1	0	0	0
4	1	0	0	0
5	1	0	0	0
6	1	0	0	0
7	1	0	0	0
8	1	0	0	0
9	1	0	0	0
10	1	0	0	0

(b) BF Events

Repetition	FF	BF	LF	SI
1	0	1	0	0
2	0	1	0	0
3	0	1	0	0
4	0	1	0	0
5	0	1	0	0
6	0	1	0	0
7	0	1	0	0
8	0	1	0	0
9	0	1	0	0
10	0	0	0	0

(c) LF Events

Repetition	FF	BF	LF	SI
1	0	0	1	0
2	0	0	1	0
3	0	0	1	0
4	0	0	1	0
5	0	0	1	0
6	0	0	1	0
7	0	0	1	0
8	0	0	1	0
9	0	0	1	0
10	0	0	1	0

(d) SI Events

Repetition	FF	BF	LF	SI
1	0	0	0	1
2	0	0	0	1
3	0	0	0	1
4	0	0	0	1
5	0	0	0	1
6	0	0	0	1
7	0	0	0	1
8	0	0	0	1
9	0	0	0	1
10	0	0	0	1

5. The Assessment Procedure

In the following notes, the measurement procedure developed to assess performances of the different classification strategies addressed in above sections, is presented.

In case of a generic Event Class E, the following quantities can be defined:

- TP (true positive): events of type E correctly recognized as belonging to class E;
- FN (false negative): events of type E recognized as belonging to a class different than E;
- TN (true negative): events different from type E correctly recognized as belonging to a class different than E;
- FP (false positive): events different from type E recognized as belonging to class E;

During the assessment procedure, the following performance indexes will be used:

- Sensitivity (S_e): the capability of an algorithm to correctly identify TPs as such.

$$S_e = \frac{TP}{TP + FN} \tag{4}$$

- Specificity (S_p): the capability of the system to correctly identify TNs as such.

$$S_p = \frac{TN}{TN + FP} \tag{5}$$

Basically, the aim of the assessment approach is to estimate the system performances in terms of reliability in fall classification.

In order to provide a fast and synthetic way to highlight the performances enhancement using the ATA as respect to simple TA algorithm, in Table 6 a comparison between the two classifiers is given. In particular, the Table shows the indexes computed for each event considered through this work and, moreover, an average evaluation of the algorithm's performances across all the classes of events (last column of the Table).

Table 6. Comparison between the TA and ATA algorithms.

Algorithm	Index	FF	BF	LF	SI	Average
TA	S_e	1	0.50	0.76	1	0.81
	S_p	0.97	1	1	0.72	0.92
ATA	S_e	1	0.89	1	1	0.97
	S_p	0.97	1	1	1	0.99

In conclusion, it can be said that there is a significant improvement in the classification performances when moving from the TA algorithm to the ATA paradigm. Values reported in Table 6, then, validate the adopted strategy while confirming the reliability of the proposed approach.

6. Conclusions

The worldwide ageing population is pushing forward the development of reliable assistive solutions for the Active Assisted Living context. Particular emphasis is given to falls which represent a serious issue which could bring catastrophic consequences. It hence emerges the need for the development of reliable and robust solutions to address the requirements of frail people willing to live autonomously. To such aim and taking into account also the need for low cost solutions, the focus of research efforts should move from very expensive hardware solutions to effective signal processing and smart computational paradigms.

In this paper, after a brief review of the State of the Art on falls recognition and classification, a case of study addressing a classification methodology exploiting a event-driven correlation paradigm and a threshold based classifier is presented. An improvement to this solution is represented by the integration of the post-fall evaluation of the accelerometer axes.

Computing the threshold values by means of the ROC curves theory further allow to make the classification methodology robust to exogenous factors. Performances of the methodology proposed have been addressed by two performances indexes, S_e and S_p, both in the case of TA and ATA algorithms. The S_e value moves from 0.81 (TA) to 0.97 (ATA). The S_p value moves from 0.92 (TA) to 0.99 (ATA). Above results state for the high reliability of the methodology developed and encourage future efforts to further extend its applicability to a wide set of events.

Author Contributions: Conceptualization, S.B.; methodology, B.A.; software and validation, R.C.; resources, V.M.; data curation, S.C.; writing–original draft preparation, R.C.; writing–review and editing, R.C.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflict of interest.

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