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A Movement Decomposition and Machine Learning-based Fall Detection System Using Wrist Wearable Device

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***Abstract*—Falls in the elderly is a world health problem. Although many fall detection solutions were presented in literature, few of them are wrist-wearable devices, mainly due to typical processing and classification challenges to achieve accuracy greater than 95%. Considering the wrist as a more comfortable, discrete and acceptable place for an elderly wearable device, this work presents the development and evaluation of a wrist-worn fall detection solution. Different sensors (accelerometer, gyroscope and magnetometer), signals (acceleration, velocity and displacement) and direction components (vertical and non-vertical) were combined and a comprehensive set of threshold-based and machine learning methods were applied in order to define the best approach for fall detection. Data was acquired for fall and non-fall movements from twenty-two volunteers. For threshold-based methods, a maximum accuracy of 91.1% was achieved with 95.8% and 86.5% of sensitivity and specificity, respectively, using Madgwick's decomposition. With the same movement decomposition and machine learning methods in the classification stage, an impressive accuracy of 99.0% was achieved, with 100% of sensitivity and 97.9% of specificity in our dataset. Prolonged tests with a volunteer wearing the fall detector also demonstrate the advantages of machine learning methods in terms of practical applications.**

***Index Terms*—Fall Detection, Machine Learning, Madgwick's Decomposition, Threshold-Based Method, Wearable Device, Wrist-Based Method.**

I. Introduction

THE average age of the world population is increasing. According to the United Nations 2015 Report for World Population Ageing, between 2015 and 2030, the number of people aged 60 years old and over is expected to grow by 56% [1]. One of the most severe problems faced by elderly people is the risk of falling. Around 30% of people aged of 65 and over fall every single year [2]. For the range of people with 85 years and over this number reaches 50%. Further, the fall recurrence is also a relevant fact. In [3], data from emergency department visitors are evaluated, identifying that 22.6% of the elderly fall victims suffered at least one new fall in six months. The recurrence is also strengthened by psychological reasons. The fear of falling and low confidence reduces elderly mobility, leading to a decreased quality of life and increased risk for new falls [4].

In order to minimize the "time to help" and fall consequences, several devices have been developed to enable the family notification of elderly emergency situations. The fall detection is normally done through many different technologies [5]. The most common one is to acquire motion information using an inertial measurement unit (IMU). IMUs are used to detect and measure a body movement with the combination of two or more sensors [6]. Typically, an IMU is comprised of an accelerometer and a gyroscope attached to the body of a person, but other sensors such as magnetometer and barometer can be included to increase the movement estimation. Using IMU data, different methods can be used to distinguish between fall and non-fall events. In this context, threshold-based and machine learning methods can be highlighted as the most frequently used classifiers for fall detection [6].

Fall detection methods based on thresholds are very common, due to the expected physical impact related to falls [7-9]. In [7], different approaches for threshold setup on fall detection solutions using accelerometer-based method are evaluated. The tests were performed considering the best specificity for an ideal sensitivity (100%) in three different body places: waist, head and wrist. Evaluating the solution with data acquired from two subjects who performed fall and Activities of Daily Life (ADLs), it was possible to achieve 100% of accuracy for the solution located at head, but only 75% at wrist. In [8], on the other hand, a threshold-based method for fall detection using the combination of accelerometer, gyroscope and magnetometer is presented. Placing the device at user's waist, the system was able to identify different characteristics of a fall event, including pre-fall analysis and aftermath position. The applied sensor fusion algorithm was the Madgwick's method [9], a simplification of Kalman-filter approach. Tests were performed with ten volunteers and the highest accuracy presented was 90.37%.

In recent works, machine learning methods appear as a new possible solution to increase detection accuracy, compared to threshold-based methods [10-17]. Particularly, a performance comparison using triaxial accelerometer data from a device

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located at user's waist is evaluated in [10]. For the evaluation, five different threshold methods and five different machine learning methods were tested with the same device under the same environment. Ten young subjects performed more than 200 fall and 200 non-fall movements. The best accuracy achieved was 96% for the machine learning method and 94% for the threshold-based algorithm. Similarly, in [13], multiple classifiers were used with differing properties, to improve fall detection and diagnostic performance using a single wearable Shimmer device (positioned at user's chest) for remote health monitoring. The final classifier, which is an ensemble of machine learning methods, obtained over 99% of overall classification accuracy, which is significantly superior in comparison to other classification methods evaluated in the presented dataset.

The final classification performance, regardless of the applied method, is highly dependent on the location of the device. In this sense, there are several works that analyze the particular case of IMU optimal location on the user's body [18-22]. In [20], for instance, a performance comparison regarding to the place where sensors can be located is presented, i.e., waist, head, wrist, front of the waist, thigh, chest, ankle, and upper arm are compared. The results indicated that chest is normally selected as an optimal, but not the most comfortable place. Wrist-based solutions are usually more accepted by users, but commonly have the worst accuracy results (e.g., less than 90%), as consequence of its high complexity motion modeling [22]. In agreement with the literature, the comparison presented in [17] and [19] showed that using IMU devices close to the patient center of gravity is the most reliable choice for spatial orientation, but also the least comfortable.

Even considering that wrist-based solutions are the most comfortable from a user point of view and less associated to the stigma of using a medical device [20,21], only a small portion of the solutions presented in literature are based on wrist-located devices. Also, relevant accuracy for practical applications (higher than 95%) is only obtained with the device located at user's ankle, trunk, chest, and waist [21]. In this sense, this work proposes a fall detector based on a wrist-located wearable device using IMU technology (accelerometer, gyroscope and magnetometer) that presents a reliable classification accuracy, i.e., sensitivity of 100% and specificity equal or higher than 95% for fall detection, resulting in a final accuracy higher than 95%. Additionally, an extensive analysis of the spatial orientation and movement decomposition in vertical and non-vertical components as a feature extraction stage for fall detection is proposed. Besides that, different classification methods based on threshold analysis and machine learning classifiers are compared, resulting in a suitable feature extraction and classification method for fall detection using a wrist wearable device.

This works is divided as follows. Section II presents the data acquisition system and evaluation protocol, whilst Section III explains the methods proposed in this work, detailing the feature extraction and classification. Section III presents the results and discussions, comparing the best achievements and defining the best approach to solve the fall detection problem. Section IV shows the conclusions and related future works.

II. Data Acquisition

For the movement signals acquisition, the GY-80 IMU device designed for embedded system application was employed. This IMU is comprised of a triaxial accelerometer (ADXL345 model), a triaxial gyroscope (L3G4200D model), and a triaxial magnetometer (HMC5883L model). The ADXL345 (Analog Devices, Norwood, MA, USA) is a low power digital accelerometer (i.e., 23 μA and 0.1 μA in measurement and standby mode, respectively) capable of triaxial measurement in ranges from ±2G to ±16G with a sample rate up to 3200Hz [23]. The L3G4200D (ST Microelectronics, Geneva, Switzerland) offers a triaxial angular velocity measurement in three different scales: 250, 500 and 2000 degrees per second. Its 16-bit resolution allows a high quality measurement, with different available sampling rate (from 100Hz to 800Hz), allowing a proper configuration for each application [24]. The HMC5883L (Honeywell, Morris Plains, NJ, USA) is a triaxial magnetometer reliable for low magnetic field measurements and able to achieve sampling rates up to 160Hz, with a 12-bit resolution and sensor field range of ±8Gauss [25].

A general property for these three described IMU sensors is the I2C communication protocol. In order to allow the acquisition and posterior analysis of the signals, an Arduino UNO development board was employed and the IMU data is sent to a personal computer, where the data can be read and analyzed with different methods developed on Matlab scripts. The IMU device and Arduino UNO were assembled into a neoprene watchband, offering a comfortable option for a wrist-worn configuration. The data was acquired with 100Hz sampling rate for all sensors, in the ranges of 4G for the accelerometer, 500 degrees/sec for the gyroscope and 0.88Ga for the magnetometer. Figure 1 shows an overview of the system.

The accelerometer, gyroscope and magnetometer signals were acquired from different volunteers simulating six fall and six non-fall activities as follow:

- Falls: forward fall, backward fall, sideways fall (to the side with the device), sideways fall (to the side without the device), fall after rotating the waist clockwise, and fall after rotating the waist counterclockwise;
- Non-Falls: walking, clapping hands, opening and closing a door, moving an object, tying shoes, and sitting on a chair.

The fall movements related to waist rotation intend to simulate a situation where the person tries to see or catch something behind him, but becomes victim of a femoral fracture, which leads to his fall. All the fall simulation movements were performed on a proper soft mattress, avoiding volunteer's injury due to physical impact. The volunteers worn the device at the non-dominant wrist. Also, the study received the approval of the Federal University of

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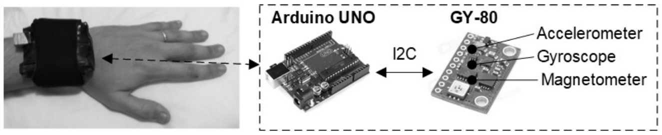

Fig. 1. Overview of the system.

Technology's (UTFPR) Human Research Ethics Committee under register number 2000216.0.0000.5547.

For this protocol, twenty-two volunteers were involved, repeating each activity three times, totaling 36 signals for each testing cycle. Thus, a total number of 792 signals become available. Half of them are related to fall simulation and half simulate activities of daily life. Each fall and non-fall signal starts with a static position (resting arms), followed by few steps before the event simulation. The average of the signals duration is 9.2 seconds. The general characteristics of the involved volunteers are:

- Age (years): 26,09 ± 4,73 years;
- Height (m): 1,68 ± 0,11;
- Weight (kg): 67,82 ± 12,24.

The acquired signals were, then, divided into two different data sets: a training set with 600 signals (approximately 75% of all data) and a testing set with the 192 remaining signals. This division was performed randomly, but assuring a same proportion of each movement type from the data acquisition protocol. Thus, the training set and testing set are comprised of 50 and 16 signals, respectively, for each one of the twelve different movement defined by the data acquisition protocol.

Unfortunately, public available datasets [26,27] are not directly applicable in our approach, due to specificity of the sensors (parameters and configurations) and experimental protocol. For example, in [26], a dataset including fall and non-fall activities was recorded, but only image and accelerometer data were acquired. On the other hand, in [27] a complete dataset with accelerometer, gyroscope and magnetometer data from participants' hand, chest and ankle was elaborated, but only ADL events were recorded.

III. Fall Detection Methods

The fall detection methods presented in this work are divided into threshold-based methods and machine learning methods. For threshold-based methods, different spatial orientation and movement decompositions are evaluated and the classification is performed using a threshold comparison, considering an optimal threshold selection. The first method, defined as *Threshold-Based Method* (TBM), employs only accelerometer and gyroscope. The second method, defined as *Threshold-based Method with Madgwick's Decomposition* (TBM-MD) uses full decomposition with accelerometer, gyroscope and magnetometer. For *Machine Learning Methods* (MLM), the above mentioned spatial orientation and movement decompositions were used with different pattern recognition classifiers. Each method is detailed as follows.

A. Threshold-based Method (TBM)

This method starts with a moving average low-pass filter with window size of 40 on acceleration values. To detect the acceleration components for the movements, the gravity value

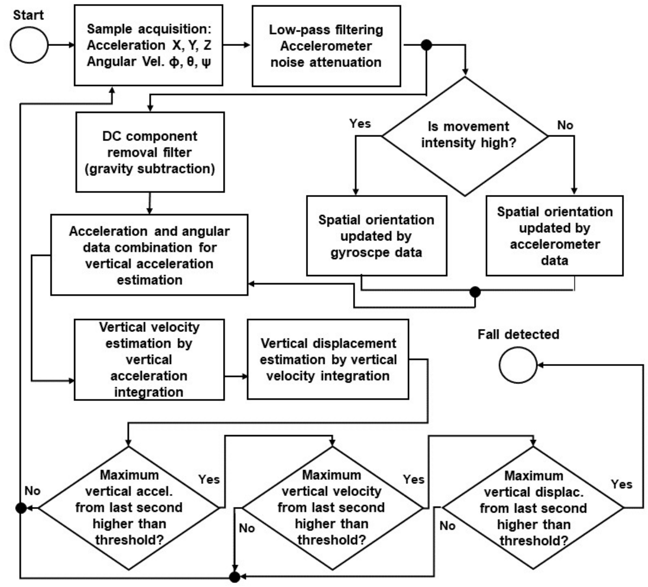

Fig. 2. Flow chart of the threshold-based method.

output is subtracted from the original measured acceleration. This allows the access to the acceleration present in each axis without information related to gravity. Such computation is done to avoid the undesirable presence of gravity acceleration in accelerometer axes due to wrist rotation.

To estimate the instantaneous movement variables of the device, a fixed value of 1G (9.8 m/s^2) is subtracted from the vector norm of the low-pass filtered acceleration data. Since 1G is the fixed expected value for the acceleration vector norm while the body is in a static position, the difference between 1G and the low-pass filtered acceleration data is related to the movement intensity of the IMU device. Eliminating the 1G offset makes easier to detect which source is more relevant for the spatial orientation estimation. If the movement intensity is low, the accelerometer information becomes valuable for this calculation. Otherwise, the use of gyroscope might become a more accurate approach. However, two difficulties are still present in this method [28].

The first is related to the spatial orientation equations. Using data from accelerometer and gyroscope, there are more than one possible solution for the angular equation, due to the gimbal lock effect [9]. Considering that the spatial orientation relevance for the method is related to the vertical component identification, the spatial orientation can be limited to a shorter range: 0º to 90º. This approach reduces the number of solutions of the angular equation, allowing the estimation of the IMU device spatial orientation. The second difficulty occurs when the measured acceleration is close to zero in one or more axis. In this case, the accelerometer noise makes the proper angular estimation challenging [28]. Therefore, in such scenarios, the gyroscope data is used for the estimation of spatial orientation instead of the accelerometer data.

A vertical component is the movement component in a direction perpendicular to the floor. For instance, while a person is clapping hands, the device would move almost only in the horizontal direction, but while a person hit a table with her hand, the device would move practically only in the vertical direction. So, the vertical analysis of the movement relies in the vertical displacement expected in a fall.

The vertical component of the acceleration data after the gravity removal may be integrated once for the vertical velocity calculation and twice for the vertical displacement calculation. In these calculations, a limited time window integration is applied to avoid the increasing noise that typically would make the resulting data useless [28].

Finally, for the proposed TBM, a fall event is considered when a given vertical displacement is identified, as a consequence of a high vertical velocity, and followed by a physical impact. Specifically, three threshold analysis are performed: acceleration, velocity and displacement. The combination of three positive detections within one second is finally considered as a fall event, as presented in Fig. 2.

To identify the best combination of signals, configuration parameters and thresholds results in the best TBM fall detection outcome, a comprehensive set of evaluations was carried out. The following six signals where evaluated to find the most relevant signals for the TBM:

- Total acceleration (TA) assuming the gravity removal;
- Vertical acceleration (VA) obtained from TA, considering vertical components only;
- Total velocity (TV) obtained from VA after time window integration of TA;
- Vertical velocity (VV) obtained from time window integration of VA;
- Total displacement (TD) from time window integration of TV; and
- Vertical displacement (VD) obtained from time window integration of VV.

A few parameter setting also plays an important role in the results. Therefore, tests were performed to find the best value choice for the following parameters:

- Time window for acceleration magnitude (TWAM): the time window size applied on the first time integration of the acceleration, allowing the selection of the spatial orientation data source (accelerometer or gyroscope);
- Lowest Acceleration Value (LAV): the smallest acceleration used for spatial orientation estimation. For values below LAV, the gyroscope data is used instead;
- Acceleration time window integration (ATWI): the time window size applied in the time integration of the acceleration (both TA and VA) to calculate velocity;
- Velocity time window integration (VTWI): the time window size applied in the time integration of the velocity (both TV and VV) to calculate displacement.

For the parameters investigation, an evaluation is performed for: four different values for TWAM, five for LAV, five for ATWI, and five for VTWI. Therefore, a total of 500 different parameters combinations were tested.

For the threshold evaluation analysis, 500 threshold values where evaluated for each of the signals, starting with a threshold where 100% of sensitivity is achieved and finishing on a threshold where 100% of specificity is achieved. Additionally, several signal combinations were evaluated: fifteen 2-by-2 signal sets, twenty 3-by-3 sets; fifteen 4-by-4 sets; six 5-by-5; and one 6-signals set.

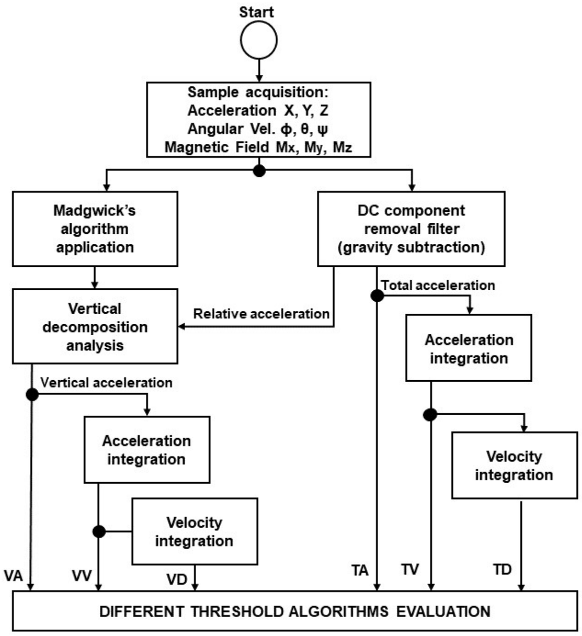

Fig. 3. Flow chart of the Madgwick's method.

B. Threshold-based Method with Madgwick's Decomposition (TBM-MD)

The Madgwick's Decomposition method using accelerometer, gyroscope and magnetometer data to calculate the unit quaternion related to the spatial orientation of a body presented in [9] was also evaluated. The quaternion $\hat{q} = \left[q_1\; q_2\; q_3\; q_4\right]$ is a four dimensional number, where q_1 is the scalar part and q_2, q_3 and q_4 are the vector parts of a 4-D complex number. Spatial orientation can be calculated from the quaternion, allowing the identification of fall detection angles in all three axes. The quaternion orientation estimation at time t (i.e., $q_{est,t}$) is computed using equation (1):

$$q_{est,t} = \hat{q}_{est,t-1} + \dot{q}_{est,t}\Delta t\,. \tag{1}$$

The $\hat{q}_{est,t-1}$ is the estimate of the orientation at a discrete time previous to T. The $\dot{q}_{est,t}$ is the estimated orientation rate and Δt is the sampling period, here considered 10ms. The estimated orientation rate, $\dot{q}_{est,t}$, is calculated by subtracting the gyroscope orientation rate from the magnitude of gyroscope measurement error, in the direction provided by accelerometer and magnetometer data. Given the quaternion $q_{est,t}$, the Yaw, Pitch and Roll angles are given in equations (2), (3) and (4), respectively:

$$\mathrm{Yaw} = \mathrm{atan2}\left(2q_2q_3 - 2q_1q_4, 2q_1^2 + 2q_2^2 - 1\right), \tag{2}$$

$$\mathrm{Pitch} = -\sin^{-1}\left(2q_2q_4 + 2q_1q_3\right), \tag{3}$$

$$\mathrm{Roll} = \mathrm{atan2}\left(2q_3q_4 - 2q_1q_2, 2q_1^2 + 2q_4^2 - 1\right). \tag{4}$$

The advantage of this decomposition is that it provides compensation for magnetic distortion and gyroscope bias drift, besides the significant reduction in computational complexity, when compared to conventional sensors fusion methods, such as the Kalman filter [8,9].

By applying the Madgwick's method, the vertical component of acceleration is computed differently from TBM decomposition and therefore, velocity and displacement might present different results. Figure 3 presents a flow chart related to the proposed TBM-MD. The TBM-MD is evaluated with the same threshold, signals and parameters selection from TBM, presented in Section II-B, to allow proper comparisons.

C. Machine Learning Methods (MLM)

The classification process with MLM includes two stages: feature extraction and the classification itself. Regarding the features, three different scenarios were evaluated. Initially, considering only the accelerometer data, the selected features were the mean and maximum values of the TA, TV and TD signals. Also, the (TA, TV), (TA, TD), (TV, TD), and (TA, TV, TD) combinations of the signals were evaluated. These tests allowed an evaluation of the classification methods when no movement decomposition was applied to the signals.

Then, the tests were performed including the gyroscope data. So, the same movement decomposition applied to the threshold-based methods was applied to MLM, allowing vertical components for feature extraction. In this case, the selected features were the mean and maximum values of VA, VV and VD. The combinations (VA, VV), (VA, VD), (VV, VD), and (VA, VV, VD) were also evaluated.

Lastly, the magnetometer information was included in the analysis. The Madgwick's method was also employed, offering a more reliable movement decomposition. Thus, the selected features for the MLM were the mean and maximum values of VA, VV and VD, but considering Madgwick's method spatial orientation. The combinations (VA, VV), (VA, VD), (VV, VD), and (VA, VV, VD) were also evaluated. Additionally, with the Madgwick's decomposition, it is possible to include the three angles related to the device spatial orientation, i.e., Yaw, Pitch and Roll. With that, some tests were performed considering the mean of sine and cosine of these angles. This information was also combined with the mean and maximum of the VA, VV and VD values, resulting in twelve features for classifiers evaluation.

Regarding the classification methods, five of the most used machine learning methods [29] for fall detection [10] were evaluated in this work, such as:

- *k-Nearest-Neighbors* (k-NN): new cases are classified according to their similarity, in terms of Euclidean distance, to the training examples. Therefore, the object is assigned to the class most common among its *k*-nearest-neighbors.
- *Linear Discriminant Analysis* (LDA): this method reduces the data to a lower dimensional space, maximizing the separation between classes, in order to reduce its complexity and required processing resource, as well as to avoid the possibility of overfitting.
- *Logistic Regression* (LR): this approach works with the relationship between the proper classification for a dataset and the different features evaluated from it, by estimating probabilities using a logistic distribution.
- *Decision Tree* (DT): DTs may be considered one of the most common method for fall detection solution presented in the literature [10]. In a DT-based method, different binary classifications are performed, considering different input features. These classifications are concatenated in a tree structure, where each node concerns about each variable and parameter evaluation. In the end, a combination of different evaluations is performed in order to obtain the final class label.
- *Support Vector Machine* (SVM): SVM was developed based on a machine learning paradigm known as statistical learning. The discrimination between pairs of classes is performed using a maximal margin classifier that is obtained by solving a convex optimization problem. Additionally, SVMs can be built in a non-linear approach, using Mercer Kernels. In this work, the Gaussian kernel was selected.

The training and testing sets are the same applied for the TBM and TBM-MD algorithms. In all experiments, the training examples are used to adjust the parameters for each classifier, by applying a five-fold cross-validation, following the procedure presented in [10]. With the best set of parameters defined with the training set, each classifier was evaluated for the testing set, allowing a proper comparison among TBM, TBM-MD and MLM.

TABLE I - EVALUATION OF DIFFERENT SIGNAL COMBINATION FOR TBM

Signal Combination	Sensitivity (%)	Specificity (%)	Accuracy (%)
(TA, TV)	**95.8**	**82.3**	**89.1**
(VA, TV)	91.7	82.3	87.0
(TA, VA, TV)	93.8	83.3	88.5
(TV)	86.5	80.2	83.3
(VA, VV, VD)	95.8	72.9	84.4

TABLE II - EVALUATION OF DIFFERENT SIGNAL COMBINATION FOR TBM-MD

Signal Combination	Sensitivity (%)	Specificity (%)	Accuracy (%)
(VA, TV)	**95.8**	**86.5**	**91.1**
(TA, VA, TV)	93.8	83.3	88.5
(VA, VV, VD)	95.8	80.2	88.0

IV. RESULTS AND DISCUSSIONS

In this section, the results and comparisons for each proposed method (TBM, TBM-MD and MLM) using the test set are presented. Table I presents the best results for the TBM, considering the threshold, signals and parameters selection presented in Section II-B. The combination of total acceleration and total velocity presents the best results with 95.8% of sensitivity and 82.3% of specificity. A similar result is obtained when the vertical acceleration is included.

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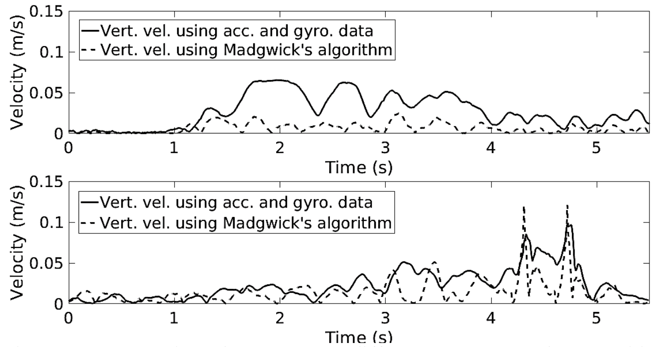

Fig. 4. Comparison between two different movement decomposition methods. The continuous line represents the resultant vertical velocity based on the decomposition considering accelerometer and gyroscope data only. The dotted line represents the resultant vertical velocity based on the Madgwick's method. On top, a non-fall signal is evaluated (less vertical movement involved), evidencing a better damping effect of the Madgwick's method. On bottom, a fall signal is evaluated and the Madgwick's method is superior again, avoiding an undesired damping effect.

Since the movement decomposition proposed for the TBM employs only accelerometer and gyroscope data, the results for vertical components of movement may present gimbal lock effect [9], and a better evaluation can be done through the employment of a magnetometer device and Madgwick's decomposition. In order to illustrate such a limitation, Figure 4 shows an example of the Madgwick's method contribution in the movement decomposition.

For a non-fall signal (top), where less vertical movement is involved, the calculated vertical velocity must present lower values than total. In that figure, a better damping effect of the Madgwick's method is evidenced. On the other hand, when a fall signal (bottom) is evaluated, a higher vertical component is expected to be measured. In the figure, the vertical velocity peak values between four and five seconds are still highlighted, while for the decomposition method based on acceleration and gyroscope data only, the peak values are damped. The difference between four and five seconds for fall and non-fall signals emphasizes the relevance of the Madgwick's method for movement decomposition, particularly for classification methods based on threshold comparison, since the peak values are greater and better characterized using Madgwick's decomposition.

In order to evaluate the possibility of increasing fall detection accuracy by combining threshold-based algorithms with Madgwick's method for spatial orientation calculation, all the configurations presented in Table I, i.e. best results for threshold-based method employing accelerometer and gyroscope data (TBM), were trained and tested including magnetometer data and Madgwick's decomposition (TBM-MD).

Initially, the combination VA and TV was evaluated and results are presented in Table II. Comparing it with the previously achieved results for TBM shown in Table I, an equal sensitivity with a higher specificity is observed. For the same configuration used in TBM, the accuracy was increased from 87.0% to 91.1% in TBM-MD. Then, the algorithm was trained and tested with the (TA, VA, TV) configuration. The achieved results were exactly the same than those presented in

TABLE III - Evaluation of Different Signal Combination For MLM

-	k-NN	LDA	LR	DT	SVM
Conf.	+Angles	(TA,VA, TV)	(VA,TV)	(VA,TV)	(VA,TV)
TP	96	95	94	94	94
TN	94	90	93	90	93
FP	2	6	3	6	3
FN	0	1	2	2	2
Sens.	100%	99.0%	97.9%	97.9%	97.9%
Spec.	97.9%	93.8%	96.9%	93.8%	96.9%
Accur.	**99.0%**	96.4%	97.4%	95.8%	97.4%

TABLE IV - Comparison of Different IMU and Wrist-based Fall Detection Solutions

Reference	Method	Configuration	Best Results
[30]	Acc. – TH	Wrist	Accur.: 65%
[31]	Acc. – TH	Wrist	Sens.: 91.3%
[7]	Acc. – TH	Waist, head and wrist	Head – Accur.: 100%
[18]	Acc. – TH	Waist, chest, wrist	Chest – Sens.: 88% Spec.:100%
[21]	Acc. - ML	Wrist	**Acur.: 94.3%**

Table I. That happened because the TA information did not add any relevant information to the final classification process. So, it was not possible to increase either sensitivity or specificity. A similar result is observed for (TA, TV) and (TV) combinations

Finally, the same configuration approached in the initial threshold-based algorithm (VA, VV, VD) was trained and tested again, in order to evaluate the evolution of this combination. The results are also presented in Table II. The achieved accuracy rate was 88%, a bit higher than the 84.4% presented in Table I. Similar to the VA, TV combination results, Madgwick's algorithm did not present an increase in sensitivity, but only in specificity rate.

Despite the improvement on the fall detection accuracy, TBM-MD was not able to allow the proposed threshold method to achieve an ideal sensitivity (100%) and the desired specificity (larger than 95%). Even employing the magnetometer data, the highest accuracy achieved was 91.1%. The misclassifications mainly included forward falls and falls with waist rotating movements that were classified as non-falls. Such misclassifications occurred only in 8.3% of the analyzed signals. Additionally, the ADL related to clapping hands was classified as fall in 81.2% of the evaluated cases, being the movement with worst classification accuracy. When a person claps hands, although the main part of the wrist acceleration is parallel to the ground, some acceleration peaks may also be measured in all three directions as a consequence of the physical impact. So, the employed threshold method is not efficient to distinguish these non-fall impacts from those related to fall events.

In order to circumvent this limitation, we propose the use of machine learning classifiers combined with Madgwick's decomposition (MLM). The best results for the MLM evaluated configurations (Section III-C) are presented in Table III. The configuration "*+Angles*" corresponds to the sine and cosine means from the three angles related to the device

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spatial orientation, additionally to the mean and maximum values of the vertical acceleration, velocity and displacement values calculated with the Madgwick's method. Such an angular information appeared to be more relevant for K-Nearest Neighbors method, allowing it to achieve 100% and 97.9% of sensitivity and specificity, respectively. Logistic Regression and SVM methods also presented relevant results: both achieved 97.4% of accuracy. LDA and Decision Tree methods presented considerably better results than those achieved by the threshold-based algorithms. Although K-Nearest Neighbors method required more input data to achieve this result (i.e., VA, VV, VD and spatial orientation angles), even when only accelerometer data was employed, relevant results can be achieved. For instance, the Logistic Regression method was able to achieve 97.9% and 95.8% of sensitivity and specificity, respectively, using only the maximum values information from accelerometer.

The misclassifications for the best model (k-NN with VA, VV, VD, and spatial orientation angles) included sitting on a chair and tying shoes. Such ADLs were classified as falls in 6.25% of the evaluated signals. This result is related to the number of neighbors selected through the applied five-fold cross-validation process, which was one for lowest cross-validation error, resulting in the nearest neighbor classifier. When only one neighbor is considered, misclassifications can occur, since falls and non-falls present overlap regions (classes are not linearly separable) in this twelve-dimensional feature space. By increasing the number of neighbors, such misclassifications can be corrected, but others may occur, such as falls that are classified as ADLs, which correspond to a more critical error from the final solution point of view.

Table IV presents a brief summary of several IMU-based fall detection solutions located at wrist described in the literature. The results are expressed according to the reported accuracy. The best reported result was obtained in [21], whose main proposal is a fall detection and ADL classification using only a digital accelerometer. The results presented in this work are potentially an improvement compared to those presented in [21] considering our data set. The lack of a standard protocol hampers a proper comparison [32], but one can state that the inclusion of the gyroscope and magnetometer data combined with acceleration, velocity and displacement signals applying movement components decomposition (vertical and non-vertical) and machine learning classifiers can improve the overall performance to achieve ideal sensitivity (100%) and specificity larger than 95%.

Finally, the proposed fall detector was evaluated for prolonged periods using the best threshold-based method and the machine learning approaches, as presented in [33], but with more ADLs and longer duration. The tests were performed by collecting data with a volunteer wearing the fall detector in six different one-hour periods. During these periods, several ADLs were performed, followed by an emulated fall in the end of each period, as follows:

- Period 1: the volunteer watches TV sitting on a couch for 10 minutes. Then, he makes a meal for about 20 minutes. In the sequence, he returns to the couch and watches TV for another 30 minutes, alternating between sitting and lying down. Finally, he lifts to walk and after a few steps, he emulates a frontal fall, lying on the ground for about 2 minutes;
- Period 2: the volunteer starts lying in a bed for a period of 25 minutes. Then, he goes to the bathroom and returns to bed for another 25-minutes period. Finally, he rises to walk and after a few steps, emulates a backward fall, lying down for about 2 minutes;
- Period 3: the volunteer starts washing dishes for 10 minutes. Then, he goes down the stairs and cleans the house for 35 minutes. In the sequence, he works in front of the computer for about 10 minutes. Finally, he emulates a sideway fall, lying down for 2 minutes;
- Period 4: the volunteer exercises for one hour at the gym, including running, walking, and sit-ups. Finally, he rises to walk and after a few steps, emulates a backward fall, lying down for about 2 minutes;
- Period 5: the volunteer performs heavy cleaning for one hour. Then, he lifts to walk and after a few steps, he emulates a frontal fall, lying on the ground for about 2 minutes;
- Period 6: the volunteer takes a bath for 15 minutes. Then, he plays guitar for 45 minutes. Finally, he emulates a sideway fall, lying down for about 2 minutes.

The best overall result was achieved by the SVM method. Only three false alarms of 9.2 seconds (analysis window presented in Section II) were observed when the volunteer moved down the stairs, 8 false alarms during physical exercises and 8 false alarms during the bath. The critical result was observed during heavy cleaning - around 90 seconds of false alarms were identified during this period. A similar result was observed for all other ML methods and TBM-MD. However, more false alarms were detected during exercises. In the particular case of TBM-MD, more than four minutes of false alarms were observed during running and sit-ups. It is important to emphasize that all the six emulated falls were correctly identified by all methods. Additionally, the average power consumption of the system during prolonged test was about 50 mA.

V. Conclusions

This work proposed the development of a fall detection system based on a wearable system located at wrist. The wrist was chosen for being considered the most discrete and comfortable place to wear a device 24 hours a day. It may also be less associated to the stigma of using a health device, allowing a higher acceptance by users.

In this sense, we presented two different approaches. The first was related to threshold-based algorithms. The best result, in this case, was achieved when Madgwick's decomposition was employed for calculating the device's vertical acceleration, and combining this information with the total velocity of the system. With that, 95.8% and 86.5% of sensitivity and specificity were achieved, respectively, leading to an accuracy of 91.1%.

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Then, five different machine learning methods were also evaluated, of which the best result was presented by k-NN method: 100% of sensitivity and 97.9% of specificity, resulting in 99% of accuracy. The results achieved by the machine learning methods were considerably higher than those achieved by the threshold-based algorithms. A similar result was observed for prolonged tests with a volunteer wearing the fall detector and performing ADLs and emulated falls. A period of around four minutes of false alarms (ADLs classified as falls) were observed for the SVM method and more than six minutes for TBM-MD, in a six-hour test.

After evaluating many different algorithms possibilities, this work concludes that machine learning approaches with the proposed movement decomposition are potentially able to achieve ideal results for a fall detection system based on a wrist-worn device The exhaustive analysis of different methods for fall detection solutions based on wrist-worn devices, which is not a common wearable configuration in literature, followed by the conclusion of MLMs as a robust approach for their development, contributes significantly to the research and development of these solutions, which allow to improve and save people lives.

The next steps of this work are related to a deeper evaluation of machine learning algorithms for fall detection and a more extensive data acquisition protocol, involving additional non-fall activities, different fall events and extensive prolonged tests. Additionally, an optimized prototype will be developed, including a detailed analysis and optimization of the consumption, size, enclosure, and other advanced prototyping features.

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