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A Movement Decomposition And Knn-Based Fall Detection

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Abstract

Aging in people makes them vulnerable to falls and this has become a universal problematic fitness issue. Literature provides several resolutions for the recognition of falls among which the wrist worn strategies are included as part of improving the output and efficacy more than that of 95%. In accordance with the theory of comfortability in the aged people, wrist is considered as the most effective area proposed for the equipment to be placed. So, the paper puts forward the idea of an apparatus to solve the mentioned issue of fall recognition. Diverse sensing units (accelerometer, gyroscope, and magnetometer), along with the indicators (acceleration, velocity, and displacement), and track apparatuses (vertical and nonvertical) are collectively used in addition to wide-ranging group of approaches involving threshold-based and machine learning theories. Therefore, it was possible to achieve superlative tactic in terms of recognizing falls. 22 individuals were chosen to learn the activities leading to fall and non-fall movements. In case of the procedures handling threshold-based idea, a maximum accuracy of 91.1% of highest exactness got accomplished in association with the acquired values of 95.8% and 86.5% in the cases of sensitivity and specificity, respectively consuming Madgwick's decomposition. About 99.0% exactness was realized by considering the identical movement decomposition and machine learning methods during the sorting period. Sensitivity and specificity were of 100% and 97.9% respectively with the established statistics.

Keywords:- Acceleration, Falls, NO- Falls, MLM.

1. 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%. 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. For the range of people with 85 years and over this number reaches 50%. Further, the fall recurrence is also a relevant fact. 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.

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. 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. 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. Fall detection methods based on thresholds are very common, due to the expected physical impact related to falls. 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. 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, a simplification of Kalman-filter approach. Tests were performed with ten volunteers and the highest accuracy presented was 90.37%.

2. TECHNOLOGIES USED

The system has two sets of approach including the hardware system based on Arduino UNO and a software simulation with MATLAB. 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.

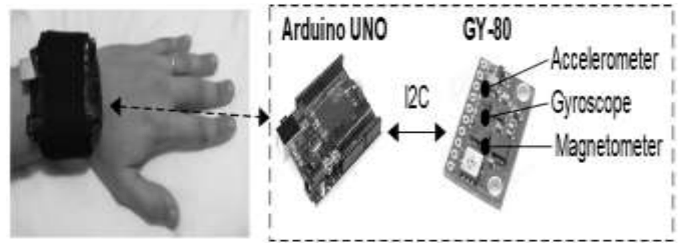

Figure 1 Overview of the system

3. IMPLEMENTATION

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. 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

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available sampling rate (from 100Hz to 800Hz), allowing a proper configuration for each application. 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.

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.

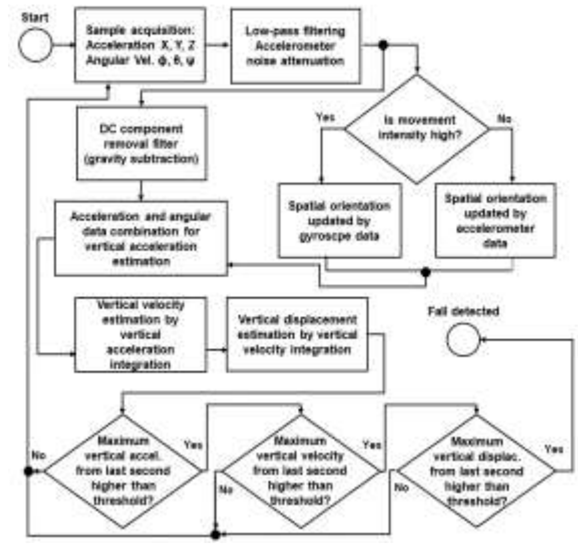

Figure 2 Flow chart of threshold-based method

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: fifteen2-by-2 signal sets, twenty 3-by-3 sets; fifteen 4-by-4 sets; six 5-by-5; and one 6-signals set.

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 ˆq = [q1 q2 q3 q4] is a four-dimensional number, where q1 is the scalar part and q2, q3 and q4 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):

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

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:

$$\text{Yaw} = \text{atan2}\left(2q_2q_3 - 2q_1q_4, 2q_1^2 + 2q_2^2 \cdot\right.$$
$$\text{Pitch} = -\sin^{-1}\left(2q_2q_4 + 2q_1q_3\right),$$
$$\text{Roll} = \text{atan2}\left(2q_3q_4 - 2q_1q_2, 2q_1^2 + 2q_4^2 \cdot\right.$$

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.

4. PROPOSED SYSTEM

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 for fall detection 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. 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

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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.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.

DISADVANTAGES

- The system can give false alarms
- Practically, it can be ineffective
- Wrist wearing can be a disturbance

5. EXPERMENTAL RESULTS

Modules incorporated in the MATLAB portion is described below.

Open Com Port

The Arduino com port is opened in this step. Port opening is required to take readings from the sensor connected to the Arduino Due. The sensor values are imported into MATLAB. A message is displayed in the command window regarding the opening of the port.

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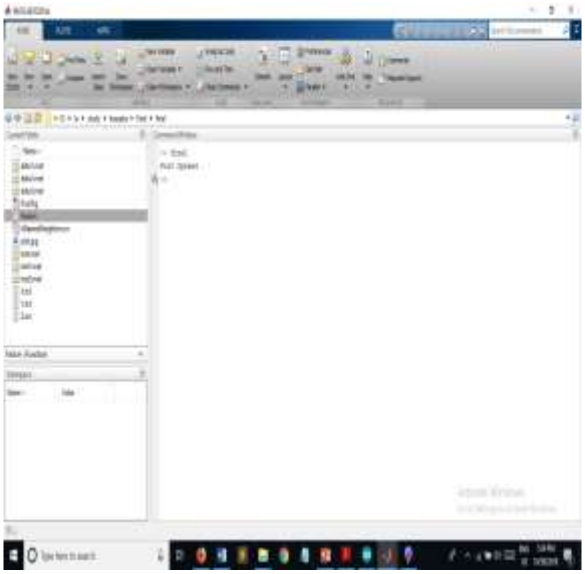
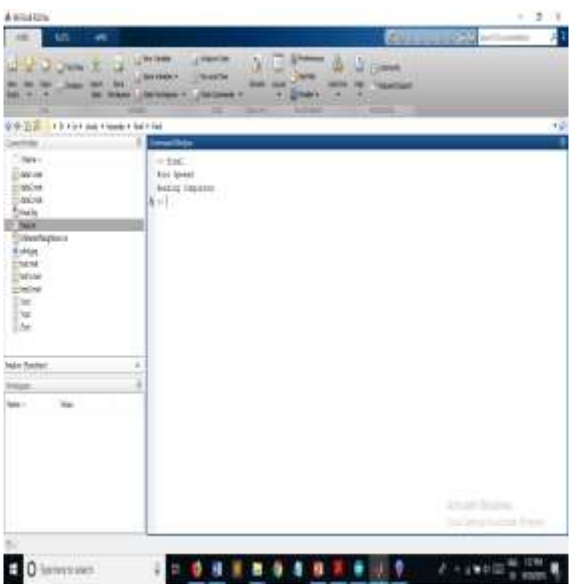


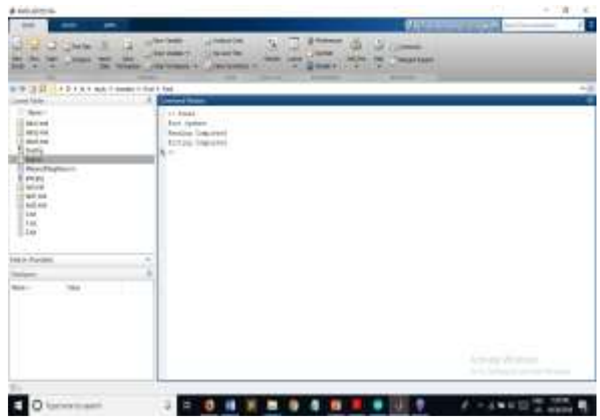
Get Readings

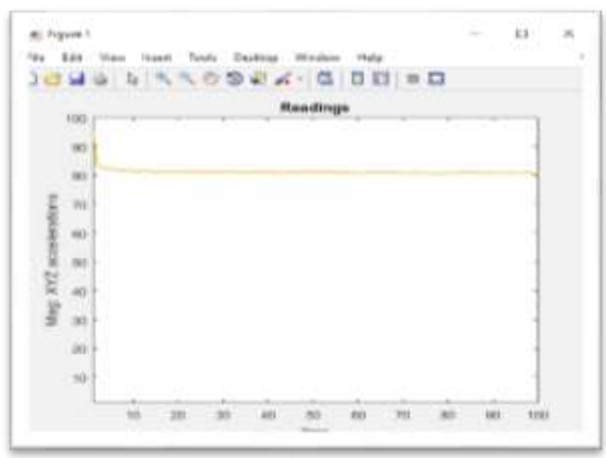
Readings are collected from the sensor and a message is displayed in the MATLAB command window after the readings are read from the port of Arduino.



Plot

The plot module enables plotting of graph based on the readings from the sensor collected from the Arduino. Message comes to the command window of MATRLAB after plotting the graph.





Apply KNN

K nearest neighbors is a simple algorithm that stores all available cases and classifies new cases based on a similarity measure (e.g., distance functions). KNN algorithm is applied to the readings and the

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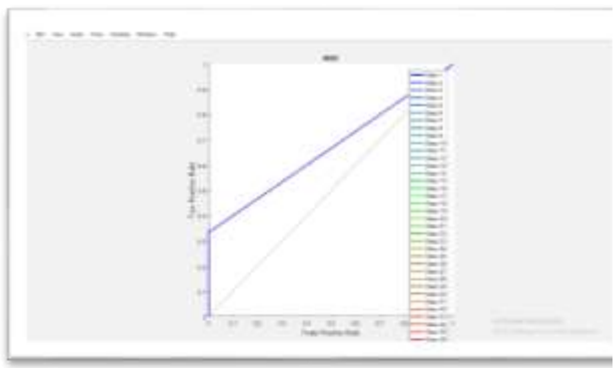
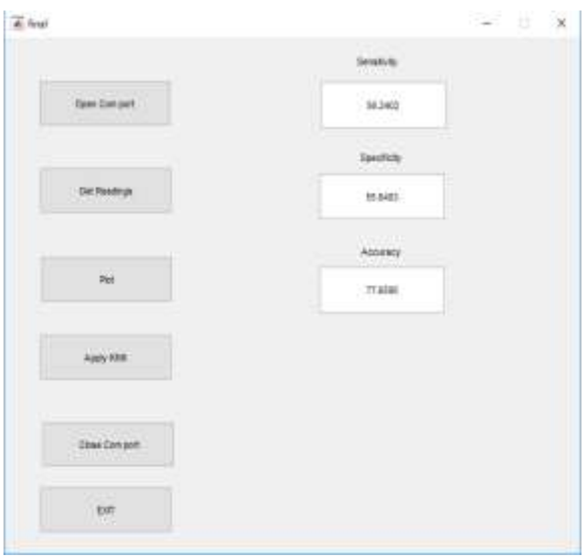
corresponding values are displayed over the command window.



Close Com Port

The close com port option stops reading from the Arduino and the process is declined.



Exit

This step gives exit for the user to come out of the system. Represents the end of the system.

6. 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.

Table 1 Evaluation of different signal com bination 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

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. 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, 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 6 shows an example of the

Madgwick's method contribution in the movement decomposition.

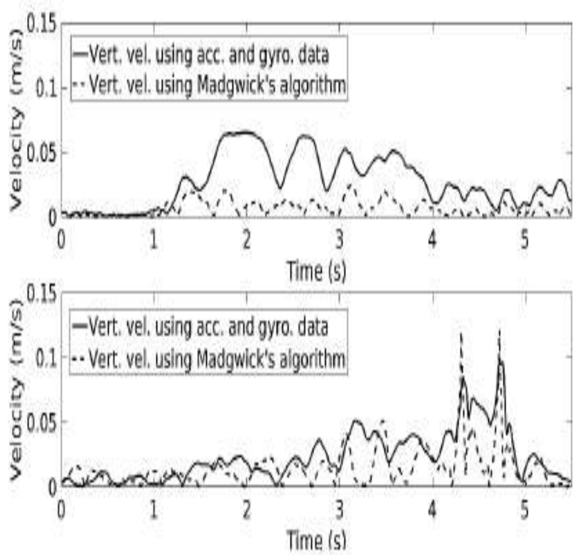


Figure 3 Comparison between two different movement decomposition

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 withMadgwick'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 2.

Table 2 Evaluation of different signal combinations 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

Comparing it with the previously achieved results for TBM shown in Table I, an equal

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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 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.

Table 3 EValuation of different signal combination for MLM

-	k-NN	LDA	LR	I
Conf.	+Angles	(TA,VA, TV)	(VA,TV)	(VA
TP	96	95	94	
TN	94	90	93	
FP	2	6	3	
FN	0	1	2	
Sens.	100%	99.0%	97.9%	97
Spec.	97.9%	93.8%	96.9%	93
Accur.	**99.0%**	96.4%	97.4%	95

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 2. 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 are presented in Table 3.

The configuration "+Angles" corresponds to the sine and cosine means from the three angles related to the device 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 fivefold cross-validation process, which was one for lowest crossvalidation 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 4 Comparison of different IMU and weist- based fall detection solution

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 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, 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 considering our data set. The lack of a standard protocol hampers a proper comparison, 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, 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.

DISADVANTAGES

- false alarms of 9.2 seconds were observed when the volunteer moved down the stairs
- false alarms during physical exercises
- false alarms during the bath
- during heavy cleaning - around 90 seconds of false alarms were identified during this period
- 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

7. CONCLUSION

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%.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 nonfall 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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