**Indonesian Journal of Electrical Engineering and Computer Science**
Vol. 43, No. 3, September 2026, pp. 726~736
ISSN: 2502-4752, DOI: 10.11591/ijeecs.v43.i3.pp726-736 

# Fall detection system based on accelerometer/gyroscope data fusion

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**Article Info**

***Article history:***

Received May 1, 2026
Revised Jul 18, 2026
Accepted Aug 19, 2026

***Keywords:***

Data fusion
Fall detection
Gyroscope
Portable system
Real-time system
Triaxial accelerometer

**ABSTRACT**

Falls are one of the major causes of death among the elderly worldwide. Faced with this public health challenge, many researchers have designed continuous monitoring systems to detect this type of incident at an earlier time, in order to facilitate immediate treatment and reduce potentially serious consequences. In this paper, we present a solution for the continuous monitoring of elderly or disabled people. We developed a fall detection system based on the fusion of data from a gyroscope and an accelerometer of a wearable inertial station. Two algorithms were developed: the first uses only the data from the gyroscope, while the second is based on the fusion of gyroscopic and accelerometric data. The evaluation of the system took into account several types of falls and activities, as well as different categories of people of different gender, age, height and weight, taken from the SISFALL database. The algorithm based on the gyroscope achieved an accuracy of 87.13% and a specificity of 84.27%, while its fusion with the accelerometer improved these performances to 90.76% and 89.92%, respectively, demonstrating the benefit of sensor fusion.

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## 1. INTRODUCTION

Activity detection and classification using sensors enable real-time and autonomous monitoring across domains like behavior analysis, elderly care, rehabilitation, and smart homes. Wearable devices, smartphones, and ambient systems integrate sensors such as accelerometers, gyroscopes, and heart rate monitors for this purpose. The collected data are preprocessed and transformed into features for human activity classification and monitoring [1]. A single sensor may be sufficient to distinguish falls, but fusion systems improve robustness and accuracy [2]. Emerging research focuses on fusion strategies that integrate sensor data, features, and classifiers to enhance diversity and generalization. Nweke *et al.* [3], a comprehensive analysis of data fusion and classification methods for activity recognition on mobile and portable devices is presented. In this context, we developed a fall detection system based on the fusion of data from a gyroscope and an accelerometer embedded in an inertial station worn by the person.

## 2. STATE OF THE ART

Fall detection relies on the use of multiple technologies to improve the accuracy and responsiveness of monitoring systems. Different types of sensors are employed to track and analyze a person's movements,

thereby enabling reliable identification of falls. One of the first studies on human fall detection based on sensor fusion was conducted in 2008 by Huang *et al.* [4], aiming to improve an intelligent cane system [5]. A first study proposed a hierarchical control scheme with estimation of the intentional direction of human movement. Subsequently, a method combining vision and laser range finder (LRF) was introduced, with fall detection based on probability density function (PDF) and simple rule-based logic. Recent fall detection systems employ various sensing modalities. For example, Boudouane *et al.* [6] combined a triaxial accelerometer with a heart rate monitor to recognize daily activities and falls, while Boudouane *et al.* [7] and Boudouane *et al.* [8] proposed a wearable camera system for elderly monitoring with privacy preservation. More recently, Newaz and Hanada [9] introduced an infrared-based approach that discriminates falls from normal activities by analyzing thermal patterns.

Researchers have explored multi-sensor systems to enhance activity classification and fall detection, often comparing them to single-sensor approaches. Unlike single-sensor methods, multi-sensor systems process each modality separately before fusing results at intermediate or final stages. Wearable accelerometers and gyroscopes, in inertial units or smartphones, provide motion data used individually or jointly for fall detection.

### 2.1. Fall detection using an accelerometer

Accelerometers are used to assess human movement, particularly gait, posture, sit-to-stand transitions, and falls. They also enable monitoring of physical activity levels and classification of daily movements. Among fall detection studies based on accelerometers, Boudouane *et al.* [10] proposed a portable real-time system for continuous monitoring of elderly or disabled individuals, using a tri-axial accelerometer and a Raspberry Pi3. Their approach relied on a multi-threshold algorithm to distinguish various types of falls and daily activities. Similarly, Makhlouf *et al.* [11]-[13] developed a multimodal system combining three ambient assistance services, including fall detection with a tri-axial accelerometer. In critical situations, an emergency service fuses the data from all three services and transmits detailed information on the user's condition to caregivers. Nahian *et al.* [14] proposed a fall detection pipeline using wearable accelerometer data, validated on three public datasets with over 7,700 features analyzed. Feature selection techniques improved performance by identifying the most relevant features. In Booranawong *et al.* [15], a real-time system using a wearable accelerometer detects stair-related activities such as ascending, descending, turning, and falling. Tested in a real home environment, it showed practical effectiveness for preventing domestic accidents.

### 2.2. Fall detection using accelerometer and gyroscope

Single-sensor systems offer high fall detection accuracy with low energy consumption, especially accelerometer-based wearables for outdoor use. Multi-sensor systems are more effective for activity classification, benefiting from complementary data [16]. Choi *et al.* [17] and Hussain *et al.* [18], the authors proposed deep learning approaches using inertial measurement unit (IMU) data (accelerometer and gyroscope) for fall and activities of daily living (ADL) classification. While Choi *et al.* [17] uses an optimized directed acyclic graph convolutional neural network (DAG-CNN), Hussain *et al.* [18] combines CNN-based feature extraction with long short-term memory (LSTM) temporal modeling to improve accuracy. Ando *et al.* [19], [20] proposed a multi-sensor fusion approach combining gyroscope and accelerometer data from smartphones and wearable devices for ADLs and fall classification. A threshold-based algorithm detects falls using acceleration and angular velocity features and automatically alerts caregivers. Research is increasingly focusing on smartphone-embedded sensors, as smartphone ownership exceeds 3 billion users worldwide [21]. Accelerometers and gyroscopes are widely used for fall detection, measuring linear acceleration and angular displacement respectively [22].

### 2.3. Synthesis

After establishing a non-exhaustive state of the art on the various existing systems, we summarized the work carried out. Indeed, wearable systems are low-cost and privacy-preserving but require continuous use and frequent charging. On the other hand, wearable systems are easy to carry and use indoors and outdoors, enabling continuous monitoring of the user [23].

Based on this synthesis, we have chosen a portable, multi-sensor system for fall detection in relation to all the ADLs performed by the user. The system proposed in this work relies on an accelerometer and a gyroscope; both sensors are low-cost components with proven effectiveness for fall detection, even when used independently. The evaluation of the system with respect to fall detection will initially be carried out using only the gyroscope. In a subsequent step, we will fuse the data from the gyroscope with those provided by the accelerometer, which were processed in the study conducted by Boudouane *et al.* [10]. This approach will enable us to assess the added value of combining the two sensors.

## 3. METHOD

Falls are distinguished from ADL by acceleration and orientation changes, detected using an accelerometer and a gyroscope. As a contribution to the development of a portable, multi-sensor fall detection system, our work proposes the use of a threshold-based method to distinguish falls from other ADLs by analyzing data from a triaxial accelerometer and gyroscope. Gyroscopes provide an alternative source of kinematic information for fall detection. With this sensor, a fall can be characterized by an increase in angular velocity, peaking when a knee or a hip hits the ground. This rotational signal captures the sudden descent of the trunk. The angular trajectory of the trunk, in sagittal and lateral directions, can be used as an additional criterion for fall detection [24]. Similarly, a high angular velocity prior to impact is a crucial marker for identifying a fall [24]. Nevertheless, a light activity such as lying down on a bed produces a similar angular velocity profile on a smaller scale. The magnitude of the angular velocity provided by the gyroscope is calculated as follows:

$$w = \sqrt{w_x^2 + w_y^2 + w_z^2} \quad (1)$$

where: $w_x, w_y \; et \; w_z$ represent the angular velocities along the three *x*, *y* and *z* axes of the gyroscope.

The gyroscopic data comes from the gyroscope integrated into an inertial station worn by the person. This sensor measures the angular velocity of body movements, enabling the detection of sudden changes in posture. In this paper, we highlight the contribution of gyroscopes to fall detection; we also show how combining gyroscopic and accelerometric data improves the reliability of fall detection systems.

## 4. IMPLEMENTATION

In this section, we first present the fall detection algorithm based on the gyroscope 'Gyro'. We then describe the fusion of gyroscope and accelerometer data using the developed algorithm 'Fusion', where the accelerometric data are obtained following the method proposed in Boudouane *et al.* [10]. Finally, we introduce the hardware system used to implement the developed algorithms.

### 4.1. Software implementation

As we noted in the previous section, we use the accelerometer to measure acceleration and the gyroscope to measure angular velocity. We detect falls using the gyroscope by analyzing the angular velocity, which then allows for subsequent fusion with the accelerometer data.

#### 4.1.1. Fall detection based on angular velocity

As presented in Section 3, the angular velocity $\boldsymbol{w}$ given by (1) becomes very high upon impact. For each sample (Figure 1), we compare the angular velocity to a threshold $\boldsymbol{S_w}$ that we determine; if the angular velocity exceeds this threshold, we say that a fall has been detected. To determine the threshold $\boldsymbol{S_w}$, we adopt the same approach developed in the work of Boudouane *et al.* [10], namely by dividing the fall dataset into two parts. The angular velocity data from the first part are used to set the threshold, while the second part and the ADL data are used to perform the tests. The threshold $\boldsymbol{S_w}$ is set to the smallest value among the highest peaks of angular velocities recorded during the fall experiments.

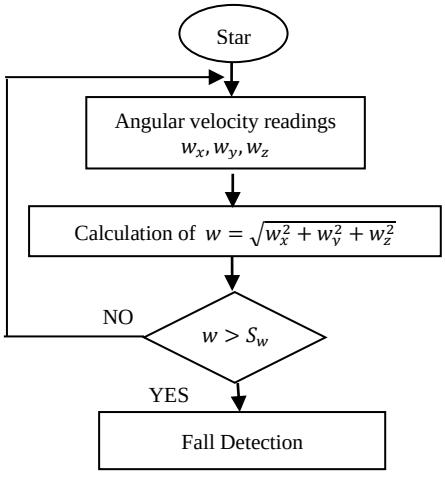


Figure 1. Flowchart of fall detection using angular velocity during the impact phase 'Gyro'

#### 4.1.2. Accelerometer and gyroscope fusion (critical phase with free fall and impact)

In this case, we will merge the data provided by the gyroscope and the accelerometer in order to improve fall detection and, in particular, reduce the false positive rate. Indeed, we use both thresholds $S_{inf}$ and $S_{sup}$ in combination with $S_w$ to detect fall events. The analysis of acceleration signals from fall activities allows defining the two thresholds: $S_{inf}$, corresponding to the lowest magnitude of the negative peaks, and $S_{sup}$, set to the lowest magnitude of the positive peaks. These thresholds are used to detect free fall and impact, respectively, in fall detection algorithms. The proposed algorithm is illustrated in Figure 2.

When the value of $A$ drops below the threshold $S_{inf}$, the data from the following second are compared to $S_{sup}$ and $S_w$ for the values of $A$ and $w$, respectively. During this period, if both $A$ and $w$ exceed $S_{sup}$ and $S_w$, a fall event is detected.

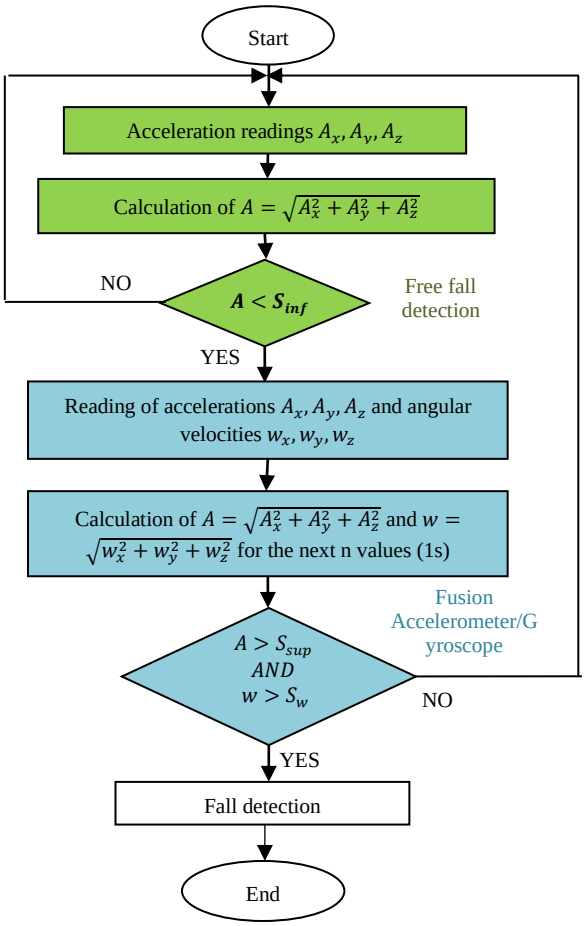


Figure 2. Flowchart of fall detection using accelerometer and gyroscope fusion 'Fusion'

### 4.2. Hardware implementation

The system proposed in this work relies on an architecture designed to continuously monitor elderly individuals or people with disabilities, both indoors and outdoors. A modular and open design was adopted, enabling the integration of additional sensors without altering the initial structure. To ensure portability, particular attention was paid to component selection in order to optimize size, weight, and power consumption.

The proposed system architecture is depicted in Figure 3. The system collects data from portable sensors, which are subsequently processed and fused to generate the appropriate actions. Our architecture is based on an inertial station composed of a triaxial accelerometer and a gyroscope, as well as an embedded Raspberry Pi 3 processor that receives the accelerometric and gyroscopic data through a wired connection. The latter are processed by the processor to detect falls using the developed and implemented algorithms. In the event of a fall detection, the communication module sends an alarm message to a PC or Smartphone to alert family members or healthcare professionals.

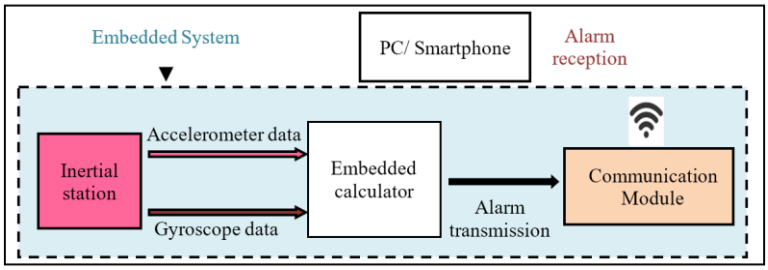


Figure 3. Proposed system architecture

## 5. EXPERIMENTAL RESULTS

### 5.1. Experimental context

The tests were carried out using the SISFALL dataset [25], which provides data from two accelerometers and a gyroscope attached to the belt, covering multiple fall and ADL scenarios, under conditions similar to our study. We used only acceleration data from the ADXL345 and angular velocity data from the ITG3200 gyroscope, with a sampling frequency of 200 Hz (one sample every 5 ms).

For the tests conducted, eight (08) scenarios were selected from 15 fall and 19 ADL scenarios, each repeated five times by 38 volunteers of different ages, heights, weights, and genders. Fall from a standing position; fall from a sitting position; lateral fall while trying to sit down or stand up; jogging; stumble while walking; sitting down and standing up quickly; trying to get up, and collapse into a chair; jumping to reach an object on a shelf. To properly evaluate the system, the five (5) selected ADLs are those that exhibit characteristics similar to falls and therefore have a high likelihood of being mistaken for them.

### 5.2. Gyroscope-based method

For these tests, 63 trials were considered for threshold detection across the selected fall types. From gyroscope signals, local maxima were identified for each fall activity, and the threshold S_w was set as the smallest of these maxima, resulting in $S_w = 250°/s$.

#### 5.2.1. Validation of the algorithm

We first validated the 'Gyro' algorithm, based on the gyroscope, for the case of a lateral fall (Figure 4), and then tested it on three types of activities, namely: Stumble while walking (Figure 5); Attempting to rise from a chair and then collapsing (Figure 6); Sitting on the edge of a chair and then standing up quickly (Figure 7).

a. Fall and stumbling while walking

In Figure 4 and Figure 5, We show the evolution of angular velocity during a lateral fall while walking and a stumble without a fall, respectively. As can be seen in Figure 4, the fall is correctly detected at time $t = 7{,}155s$ with an angular velocity of $409°/s$ which exceeds the threshold $S_w$. Figure 5 shows a Stumble without a fall. In this figure, we observe a sudden increase in angular velocity; however, it does not reach the threshold $S_w$. As a result, the algorithm does not detect a fall and therefore does not introduce a false positive for this activity, which had been detected as a fall when using the accelerometer-based method.

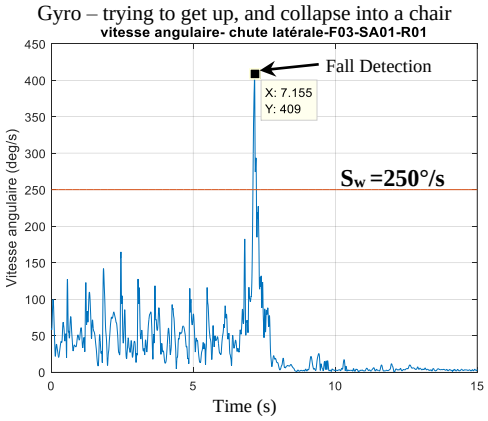


Figure 4. Evolution of angular velocity during walking

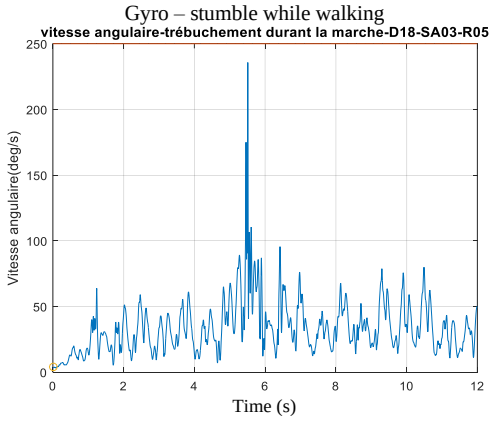


Figure 5. Evolution of angular velocity for a stumble while walking

b. Activities “collapsing onto a chair” and “sitting down and standing up quickly”

Figures 6 and 7 show the evolution of angular velocity for the two ADLs “trying to get up, and collapse into a chair” and “sitting down and standing up quickly”, which were falsely detected as falls by the accelerometer-based method.

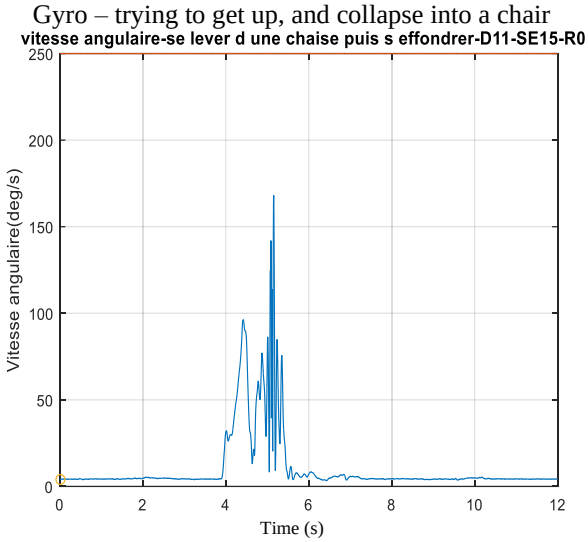


Figure 6. Evolution of angular velocity for the ADL ‘Trying to get up, and collapse into a chair’

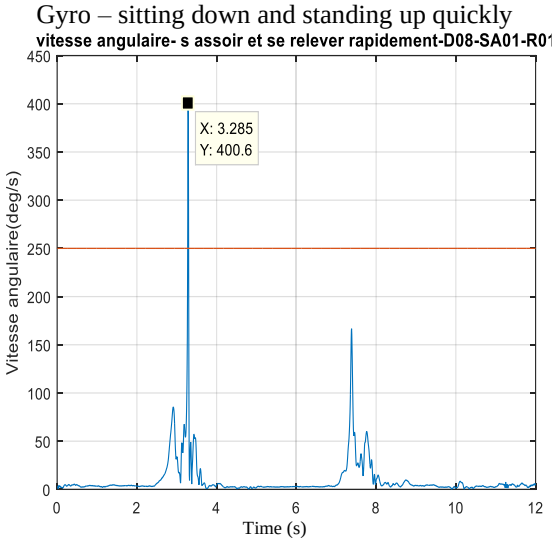


Figure 7. Evolution of angular velocity for the ADL ‘Sitting down and standing up quickly’

For the first activity (Figure 6), the angular velocity peak remains below the threshold $S_w$, allowing the algorithm to eliminate the false detection from the accelerometer-based ‘Acc’ method. For the second activity (Figure 7), it fails to remove a false positive, detecting a fall at $t = 3{,}285s$ with an angular velocity of $400{,}6°/s$ which exceeds $S_w = 250°/s$ by $150°/s$.

### 5.2.2. Performance evaluation

To evaluate the performance of the gyroscope-based fall detection method and compare it with the accelerometer-based method [10], we used the same set of test data for both falls and ADLs. The test results, along with the calculation of performance metrics, are presented in Table 1. As shown in the Table 1, all falls were detected using the gyroscope-based method, resulting in a sensitivity of 100%. Indeed, our analysis of the test results revealed that all falls missed by the accelerometer-based algorithm, which had a sensitivity of 91%, were correctly detected as falls by the gyroscope-based method.

Regarding the elimination of false positives introduced by certain ADLs, the specificity achieved was 84.27%, which is higher than that obtained with the ‘Acc’ algorithm, which was 71.37%. Similarly, the accuracy calculated for the gyroscope-based method was 87.13%, exceeding by 12.22% the value obtained with the accelerometer-based algorithm ‘Acc’.

Table 1. Performance of the gyroscope-based algorithm

| Gyro | Falls | ADLs |
|---|---|---|
| True positives (TP) | 55 | - |
| TP+ false negatives (FN) | 55 | - |
| Sensitivity = TP/(TP +FN) | 100% | - |
| True negatives (TN) | - | 209 |
| TN+ false positives (FP) | - | 248 |
| Specificity = TN/(TN +FP) | - | 84,27% |
| Accuracy | 87,13% | |

### 5.3. Fusion gyroscope/accelerometer

The algorithm based on the fusion of gyroscopic and accelerometric data declares a fall only if it is detected from both the gyroscope and accelerometer data, almost simultaneously within a time interval not

exceeding 0,5s. Similarly, the same procedure was followed to determine the thresholds $S_{inf}$ and $S_{sup}$. Based on the analysis of the accelerometer signals, we set $S_{inf} = 0{,}8g$ and $S_{sup} = 3{,}07g$, values chosen to effectively distinguish between normal activities and fall events.

### 5.3.1. Validation of the algorithm

To validate the 'Fusion' algorithm, we present the following test cases:

- A vertical fall while walking, which was correctly detected by both the accelerometer-based and gyroscope-based methods individually.
- The activity of jumping to reach an object, which was falsely detected as a fall by the accelerometer-based method but correctly identified as a non-fall by the gyroscope-based method.

Figures 8 and 9 respectively illustrate the graphs of the accelerometer and gyroscope signals during the execution of these two activities.

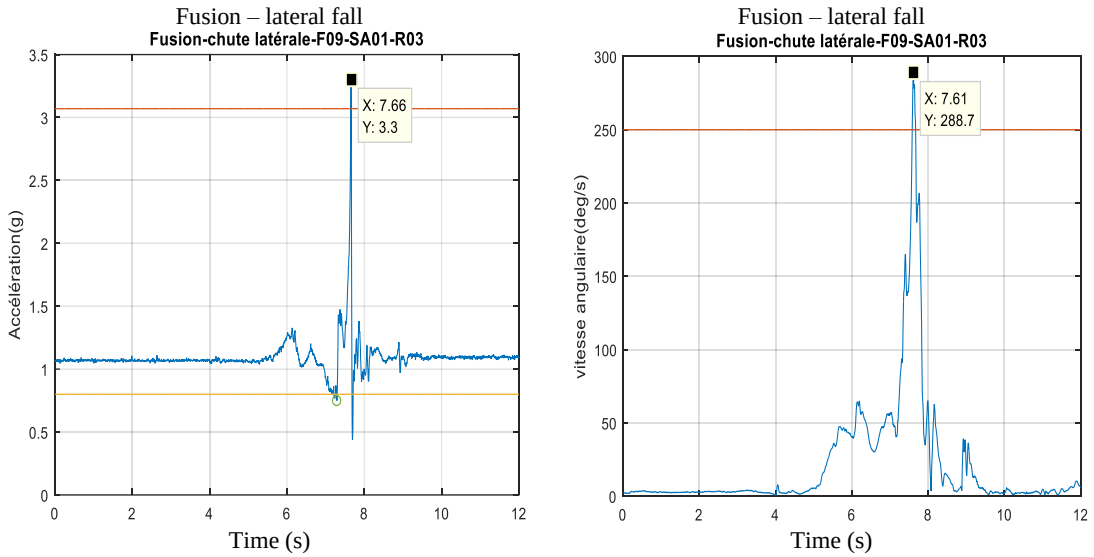


Figure 8. Evolution of angular velocity for a lateral fall

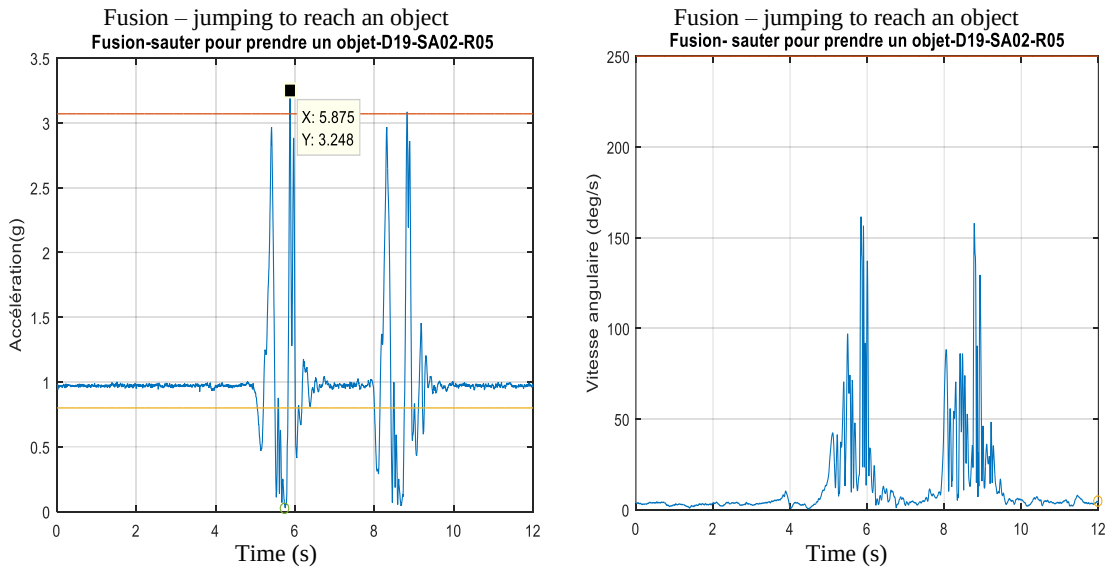


Figure 9. Evolution of angular velocity for the ADL 'jumping to reach an object'

The indications in Figure 8 show that the acceleration and gyroscope signals fall below $S_{inf}$ and exceed $S_{sup}$ and $S_w$ during the fall. When the fall event occurs, the acceleration signal decreases from $\sim 1g$ *to* $\sim 0{,}75g$, falling below $S_{inf}$ $(0{,}8g)$. Then, after $0{,}36s$, the acceleration and angular velocity signals rise to $\sim 3{,}3g$ and $\sim 290°/g$, respectively, exceeding $S_{sup}$ (3.07 g) and $S_w$ $(250°/\mathrm{s})$ within a time interval of $0{,}05s$, which is shorter than the set interval of $0{,}5s$, thus allowing the fall to be declared.

In Figure 9, we show that the fusion algorithm eliminates the false positive introduced by the activity "jumping to reach an object." Indeed, the detection of the acceleration peak, which reaches $\sim 3{,}25g$ and exceeds $S_{sup}$, does not coincide with the gyroscope velocity of $\sim 161°/s$, which remains well below $S_w$.

### 5.3.2. Performance evaluation

The tests for all algorithms were conducted on the same dataset for both falls and ADLs; we therefore applied the fusion algorithm directly to this same set. Table 2 presents the test results along with the performance metrics. As can be seen in Table 2, fusing the accelerometer and gyroscope data improved the system's performance metrics. Indeed, the accuracy achieved, 90.76%, is higher than that obtained by the accelerometer and gyroscope individually, which were 74.91% and 87.13%, respectively. The specificity also increased to 89.92% using fusion, compared to 71.37% for the accelerometer and 84.27% for the gyroscope. Regarding sensitivity, the value obtained with fusion is 95%; this is higher than that of the accelerometer alone (91%) but lower than that of the gyroscope (100%).

Table 2. Performance of the fusion-based algorithm

| Gyro | Falls | ADLs |
|---|---|---|
| TP | 52 | - |
| TP+FN | 55 | - |
| Sensitivity =TP/(TP+FN) | 95% | - |
| TN | - | 223 |
| TN+FP | - | 248 |
| Specificity =TN/(TN+FP) | - | 89,92% |
| Accuracy | 90,76% | |

## 5.4. Discussion

The percentages of the three performance metrics for the accelerometer-based and gyroscope-based fall detection methods, as well as their fusion, are shown in the graph in Figure 10. In this work, we developed a fall detection system primarily based on the use of the gyroscope. The 'Gyro' algorithm applied to these data achieved a sensitivity of 100%, thereby detecting all falls. However, this approach led to a slight decrease in specificity, which affected the overall accuracy (87.13%). The 'Fusion' algorithm, combining gyroscope and accelerometer data, leveraged the strengths of each sensor: the specificity provided by the accelerometer and the sensitivity of the gyroscope. This combination resulted in a significant improvement in performance, with accuracy reaching 90.76% and specificity 89.92%.

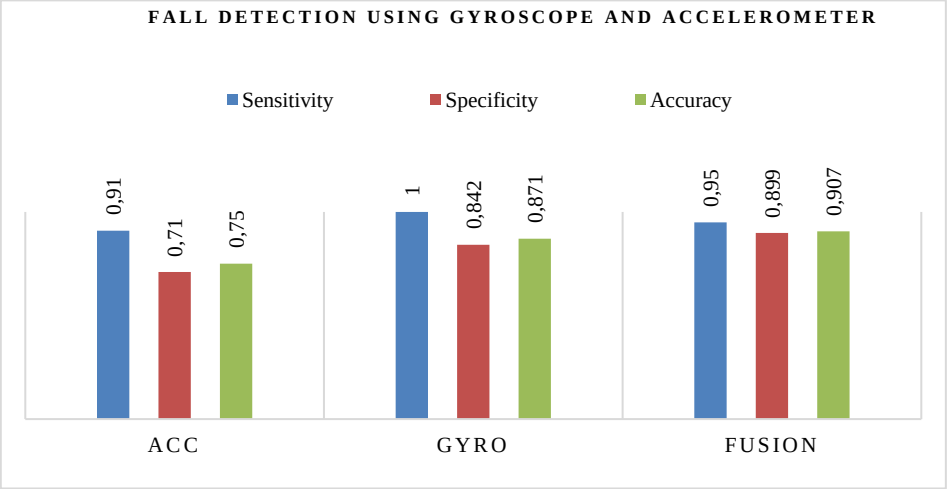


Figure 10. System performance representation

## 6. CONCLUSION

In this paper, we present a solution designed to ensure continuous monitoring of elderly people or individuals with disabilities, whether they live alone at home, in nursing homes, in hospitals, or outdoors environments. The objective is to rapidly detect potential falls in order to enable immediate action, with maximum accuracy and minimal false alarms. We developed a fall detection system based on the fusion of data from a gyroscope and an accelerometer within a portable inertial station.

To enable seamless integration into mobile devices, we designed an optimized architecture that minimizes memory usage while ensuring reliable real-time fall detection. The algorithm based solely on the gyroscope achieved satisfactory results in terms of accuracy and specificity. However, the approach combining gyroscope and accelerometer data delivered significantly better performance, thereby confirming the effectiveness of sensor fusion for more robust and reliable fall detection.

The fusion of gyroscope and accelerometer data was implemented to enhance fall detection accuracy. A more advanced fusion strategy could further integrate post-fall time and body orientation. Moreover, since these sensors are commonly embedded in Smartphones, the proposed approach offers strong potential for practical implementation on widely used mobile devices.

## FUNDING INFORMATION

Authors state no funding involved.

## AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

| Name of Author | C | M | So | Va | Fo | I | R | D | O | E | Vi | Su | P | Fu |
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| Amar Ramdane-Cherif | | | | | | | | | | | ✓ | ✓ | | |

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

## CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

## DATA AVAILABILITY

The data that support the findings of this study are openly available in the SisFall dataset [25].

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