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Tecnura

https://revistas.udistrital.edu.co/ojs/index.php/Tecnura/issue/view/1214
DOI: https://doi.org/10.14483/22487638.22066

INVESTIGACIÓN

Pre-and-post impact fall detection based on support vector machines using inertial and barometric pressure data

Detección de caídas con máquinas de soporte vectorial identificando pre y post impacto con datos inerciales y presión barométrica

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Fecha de Recepción: 30 de enero de 2023 **Fecha de Aceptación**: 18 de abril de 2024

Cómo citar: Roberth Álvarez Jiménez, Edith Pulido Herrera, Andrés F. Ruiz-Olaya,Daniel Alfonso Sierra Bueno (2022). Pre-and-post impact fall detection based on support vector machines using inertial and barometric pressure data. *Tecnura*, **28**(78), 34-52. https://doi.org/10.14483/22487638.22066

ABSTRACT

Objective: This paper presents a novel real-time algorithm for fall detection, which contextualizes falls by identifying activities occurring both pre- and post-impact utilizing machine learning techniques and wearable sensors.

Methodology: The activities selected to contextualize fall events included standing, lying, walking, running, climbing stairs, and using the elevator. Data were collected using an inertial measurement unit and a barometric altimeter positioned on the participants' lower backs. Thirteen healthy subjects were observed performing the activities and fall events were recorded from five healthy subjects. The proposed algorithm combines thresholding and cascade support vector machines (SVMs), whose robustness is enhanced by a verification process of the subject's posture aimed at determining the occurrence of the fall more accurately.

Results: The performance of the algorithm was evaluated in terms of the hit rate (HT) both offline and in real-time. From the activities studied, stairs climbing proved to be the most challenging to detect, with an offline HT of 85 % and an online HT of 76 %. The overall offline performance was superior, with an HT of 96 %, compared to the performance achieved online, an HT of 91 %; in both cases the fall detection HT was 100 %.

Conclusions: The algorithm can be used to recognize fall events occurring to any user, as it has the advantage of not needing prior adaptation due to the nonlinear nature of the SVMs. The cascade SVMs allow for using small sets of variables,

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leading to low computational cost and a suitable real-time implementation. These features, in addition to the posture verification process, make our algorithm suitable for activity recognition in non-laboratory environments.
Financing: This research was partly funded by the Colombian Administrative Department of Science, Technology, and Innovation (COLCIENCIAS) and the Universidad Industrial de Santander (UIS), grant FP44842-507-2014, project 1817; and by the Universidad El Bosque under grant PCI2019-10784.

Keywords: support vector machines, activity recognition, fall detection, wearable inertial sensors, pre-and-post impact.

RESUMEN

Objetivo: Este artículo presenta un algoritmo para la detección de caídas en tiempo real, el cual se contextualiza mediante el reconocimiento de las actividades previas y posteriores al impacto de la caída, utilizando técnicas de aprendizaje automático y sensores llevables.
Metodología: Las actividades estudiadas para la contextualización de la caída incluyen estar de pie, caminar, correr, subir o bajar en escaleras, y desplazarse en ascensor. La recolección de datos se hizo utilizando una unidad de medición inercial y un barómetro ubicados en la parte baja de la espalda de los participantes. Trece voluntarios sanos fueron observados para el registro de actividades y cinco voluntarios sanos para el registro de las caídas. El algoritmo propuesto combina máquinas de vectores de soporte (SVM) en cascada y umbrales, cuya robustez es mejorada con un proceso de verificación de la postura del sujeto para determinar de manera más precisa la ocurrencia de la caída.
Resultados: El rendimiento del algoritmo fue evaluado en términos de la tasa de aciertos (TA) tanto *offline* como en tiempo real de detección de las actividades estudiadas. Subir o bajar escaleras representó lamayor dificultad de detección, con una TA del 85 % *offline* y del 76 % *online*. El rendimiento global *offline* fue superior, con una TA del 96 %, comparado con el rendimiento alcanzado *online* , representado por una TA del 91 %; en ambos casos la TA de detección de caídas fue del 100 %.
Conclusiones: El algoritmo puede utilizarse para reconocer eventos en cualquier usuario, es decir, tiene la ventaja de no requerir adaptación previa, dada la naturaleza no lineal de las SVM. Las SVM en cascada permiten el uso de pequeños conjuntos de variables, lo que genera un bajo costo computacional y una implementación adecuada en tiempo real. Estas características, además de la robustez incrementada con un proceso de verificación de postura con excelentes resultados en la detección de la caída, permiten que nuestro algoritmo sea adecuado para el reconocimiento de actividades en entornos fuera del laboratorio.
Financiamiento: Esta investigación fue parcialmente financiada por Colciencias, actualmente Ministerio de Ciencia Tecnología e Innovación y la Universidad Industrial de Santander con el contrato FP44842-507-2014, proyecto 1817; y la Universidad El Bosque con el proyecto PCI2019-10784.

Palabras clave: máquinas de soporte vectorial, reconocimiento de actividades, detección de caídas, sensores llevables inerciales, pre-post impacto.

INTRODUCTION

Falls are the second leading cause of death due to unintentional injuries in older (aged over 65) populations (James *et al.*, 2019). Each year, approximately 28–35 % of individuals aged 65 experience falls, while the figure rises to 32–42 % among those aged over 65 (World Health Organization, 2007).

Even non-fatal falls can result in injuries such as fractures or moderate to severe traumatic brain injuries, significantly impacting individuals' well-being. Long lies following a fall can seriously affect the physical and psychological condition of the elderly. For instance, 47 % of older adults are unable to get up after a fall (Tinetti *et al.*, 1993), and some studies indicate that half of those who remain on the floor for more than an hour might die within six months (Wild *et al.*, 1981). Periodic assessments of daily physical activities would facilitate ongoing objective monitoring to identify fall risks. Extensive research has been conducted to assist individuals during fall incidents. However, there remain unresolved issues related to accurately detecting falls or excessively yielding false alarms that can overwhelm caretakers and caregivers alike. In both scenarios, confidence in the technology may wane, affecting its acceptance among final users (Igual *et. al.*, 2013).

Fall detection systems utilize sensor technology such as acoustic, floor pressure, near field imaging, vision, ultrasonic, radar, barometers, or wearable inertial sensors (Nooruddin *et al.*, 2021). Miniaturized sensors like wearable barometers or inertial sensors have recently gained significant attention. Their cost and portability offer the opportunity to monitor potential fallers on a daily basis, i.e., outside clinical settings. These sensors can be placed on various parts of the body, including the head, chest, wrist, trunk, feet,ankle, among others, allowing valuable information about falls and motion activities to be gathered (Alvarez *et al.*, 2017; Alvarez, 2017; Patel*et al.*, 2020). This range of possibilities allows for comparing the performance of the various approaches regarding sensor location (Kangas, 2008). Nonetheless, studies have shown that relying on only one location may be sufficient to recognize human locomotion-related activities. In this respect, when using inertial sensors individually, the lower back emerges as the most common body location because the center of mass of the human body is in this area (Inman *et al.*, 2006), which facilitates the recognition of human locomotion related activities in free-living environments.

Data processing algorithms include the analysis of parameters such as the accelerations or angular velocities in the axes of movement of the human body, changes of height during falls, or vertical velocity, among others (Zhang *et al.*, 2006; Sabatini *et al.*, 2016). These approaches are based on analytic and learning techniques (Noury *et al.*, 2007). Analytic methods consist of merging data from different sensor technologies to which thresholding methods are applied. Accelerations thresholds are the most common criteria associated with fall events and motion-related activities such as walking or jumping. In order to process such information, machine learning is commonly utilized through techniques such as support vector machines (SVM), k-nearest neighbors (K-NN), and deep neural networks (Yu *et al*., 2020).

Most algorithms commonly discriminate falls from non-falls or falls from motion activities (e.g., walking, running). Yet, few studies have addressed fall detection by contextualizing the fall event. To bridge this gap, one strategy could be to identify pre- and post-impact fall activities (Lopez-Yunez *et al*., 2014; Pierleoni *et al*., 2015). This approach can help in properly managing the fall event to avoid harmful consequences such as prolonged immobility. By contextualizing the event, we can regard scenarios that involve changes between postures and activities, e.g., sitting to standing or walking to running. Importantly, when discriminating falls from other activities, systems can erroneously associate activities that present similar signal patterns, in short periods, with falls, e.g., walking upstairs, downstairs, or running. These misidentifications can increase the rate of false positives. To address this issue and drawing inspiration from the work of Sorvala *et al.* (2012), we propose a hybrid algorithm for fall detection that contextualizes the event through the recognition of pre-impact and post-impact fall activities using inertial and pressure data. The activities are defined considering typical motion scenarios observed in the daily activities of common users. The algorithm combines thresholding and two cascade support vector machines (SVMs). Moreover, to increase the robustness of the fall detection, a verification process consisting of three stages is included: detection of a possible fall, verification of the previous activity, and assessment of the current posture to determine whether to trigger a fall alarm.

MOTION ACTIVITIES AND FALL CHARACTERIZATION

Falls can occur in scenarios where individuals intentionally or unintentionally change their body position, for instance, going to bed or losing balance during a walk. A fall event can be characterized as having four stages: start, impact, post-impact, and posture (Pierleoni *et al*., 2015). These stages can be well interpreted from the vertical acceleration pattern when using a body-waist accelerometer. As illustrated in Figure **1** and Figure **2**, the acceleration exhibits significant variations in its values, reaching sudden high magnitudes when the impact occurs. Subsequently, in the post-impact and posture stages, the magnitudes may vary according to the individual's recovery.

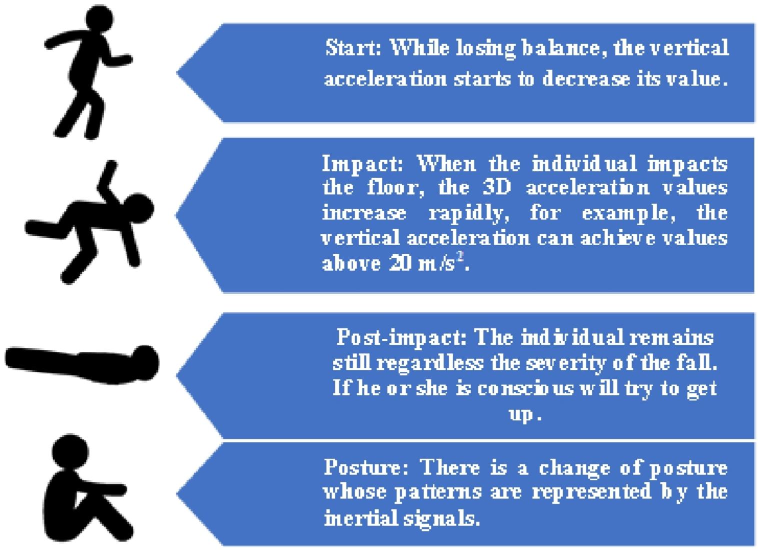


Figure 1. Characterized phases of a fall.

Source: Adapted from (Pierleoni *et al.*, 2015).

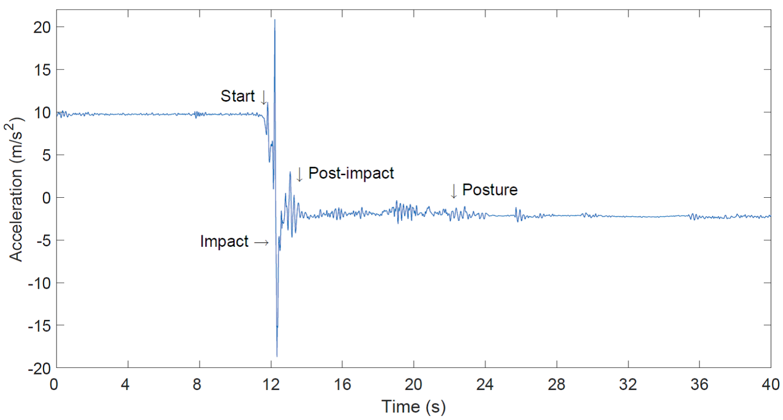
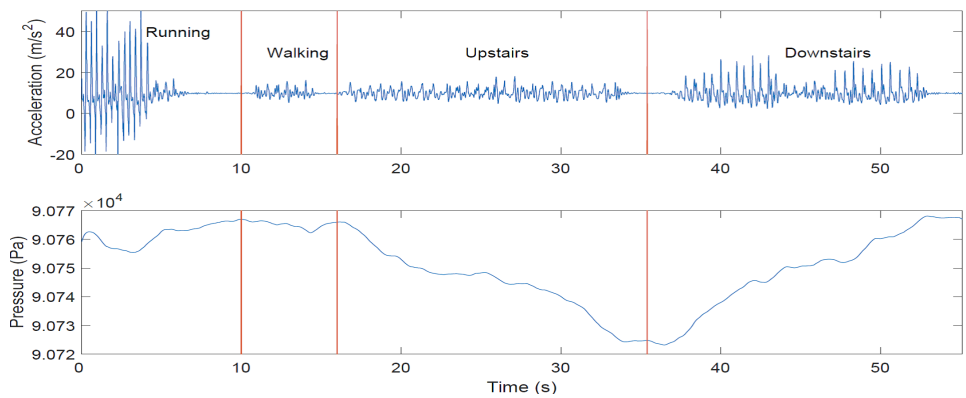


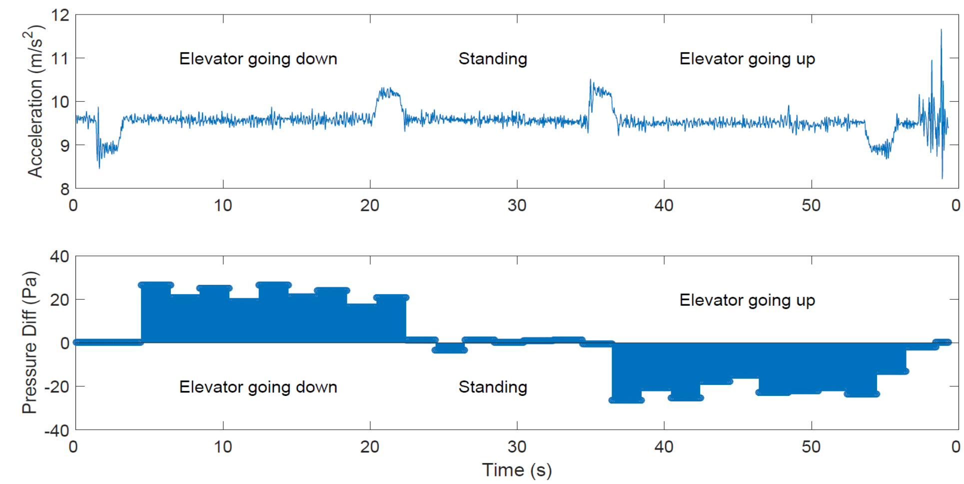
Figure 2. Vertical acceleration pattern during a fall.)

Source: Authors' elaboration.

Considering a real-life scenario, we choose a set of activities that may occur before and after a fall event. Specifically, we included postures and motion activities such as standing, walking, running, ascending and descending stairs, and using the elevator. To characterize these activities, we employed motion and height data. Figure 3a shows the patterns of vertical acceleration and pressure of a user performing various activities. As observed, running and walking upstairs and downstairs present high peaks of the vertical acceleration, while pressure data hardly showed identifiable patterns for most activities. Nonetheless, since pressure data allows for identifying changes in height, it can be useful in identifying climbing stairs and using an elevator, as is shown in Figure 3b.



(a)



(b)

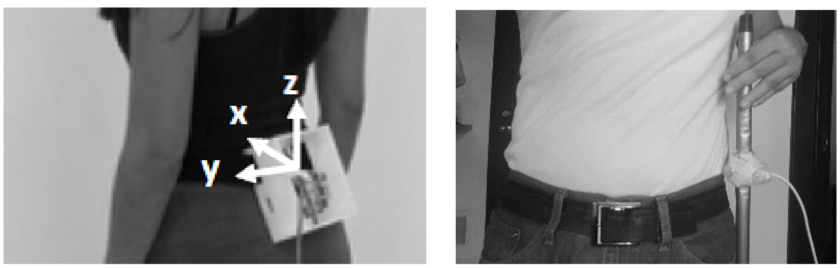
Figure 3. a) Vertical acceleration and pressure signals during the following activities: walking, running, and walking upstairs or downstairs. b) Vertical acceleration and pressure signals for walking and walking upstairs or downstairs

Source: Authors' elaboration.

METHODOLOGY

Participants and equipment setup

Falls and activities signals were collected from 13 volunteers (8 women, 5 men, aged 20 to 25 years). The university's ethical committee approved the experiment protocol and all participants signed the informed consent form. Motion data were collected using an embedded prototype (Bravo, 2017) compounded of a Beagle Bone Black Board, which processed data from an IMU-I manufactured by Xsens and the Pololu-brand Alt-IMU V4. Sensors were placed on participants' lower back (see Figure **4**a). The IMU measures acceleration and angular velocity in 3D with a sample frequency fs = 50Hz. The Alt-IMU measures the pressure with a sample frequency fs = 25Hz. Another setup was designed to collect fall data, involving the attachment of the IMU to a waist-level bar (see Figure **4**b) (Kumar, 2013).



a) b)

Figure 4. a) System located at the lower back for data acquisition. b) IMU placement on a waist-level bar.

Source: Authors' elaboration.

Data sets

Offline testing protocol: A first protocol was designed for the purpose of training the two support vector machines intended to classify falls from other activities, as described in the *Algorithm Overview* section. Accordingly, the following set of tasks was defined: (1) *straight-line walk I*: participants were asked to walk 30 steps in a straight line at a self-paced speed; (2) *straight line walk II*: participants were asked to run 30 steps; (3) *walking up and down the stairs*: participants were asked to ascend 15 steps and then descend 15 steps; this task was repeated four times; (4) *sit/standing*: participants were instructed to sit, wait for about 3 seconds, and then stand up; this tas

Fall data were collected through two experiments. The first experiment consisted in dropping a bar (see Figure **4**b) onto a mattress ten times. In the second experiment, 5 participants were asked to fall forward onto a mattress twice (see Figure **5**).

Figure 5. A sequence of a fall event test conducted by a participant.

Source: Authors' elaboration.

Real-time testing protocol: This protocol was designed to conduct real-time experiments that replicate common scenarios for activity and fall detection. Participants performed a first set of activities as follows: (1) *activities*: they began with a 15-meter walk, paused in front of stairs for about 5 seconds, proceeded to climb the stairs (about 3 meters), then walk downstairs , and waited for about 5s. Next, they turned around and repeated the same movements, in addition of running in the last segment of the path; and (2) *elevator use*: a participant was asked to ride the elevator up and down a few times.

The second set of tests was designed to evaluate the performance of the fall detection algorithm. As such, participants simulated falls in various scenarios by performing the following tasks: *test 1*: the participant was instructed to first to stand, then fall onto a mattress, and remain lying down for a few seconds (see Figure **5**); *test 2*: the participant walked to the mattress, fell onto it, and remained lying down until he was instructed to sit; *test 3*: the participant walked to the mattress, then fell onto it, got up, and resumed walking.

Test 1 and test 2 simulate situations where the algorithm is expected to detect a fall, considering post-impact conditions, as the subject remains on the floor. Test 3 replicates a situation where the subject falls but manages to return to a normal position and continue moving.

Feature extraction

A feature extraction process was carried out using data collected during the offline protocol to identify the best features in the classification process. Time-domain features were extracted every 2 seconds from the raw acceleration and angular velocity collected with a frequency of 50 Hz, and the pressure data collected with a frequency of 25Hz. The pressure data were low-pass filtered using a second-order Butterworth filter with a 0.3Hz cut-off frequency. Features derived from the acceleration, angular velocity in 3D, and their magnitudes were the maximum, the minimum, the mean, the standard deviation, the variance, and the root mean square. The differential pressure was a feature derived from the pressure data. As such, 170 features were obtained, which underwent a forward selection process using Matlab. As a result, the features that presented the best separability for falls and “other activities-1” (activities with displacement) were the minimum and the maximum of the lateral angular velocity (ω_y); and the variance of the magnitude of the acceleration $var\,(a_{mag})$. For walking and “other activities-2” (activities with higher peaks, i.e., running or walking upstairs and downstairs), the features that presented the better performance were the variance of the acceleration magnitude $var\,(a_{mag})$; and the variance of the forward acceleration $var\,(a_x)$. The final set of features was used to train and validate a cascade of two support vector machines, as will be described in the following sections.

ALGORITHM OVERVIEW

The algorithm combines heuristics knowledge and learning techniques to classify falls and activities. Namely, the algorithm is based on thresholding methods, i.e., Decision Making I and Decision Making II; and two support vector machines (SVMs) in cascade, SVM-1 and SVM-2 (see Figure 6). Both classifiers were trained with the features previously obtained, validated using 10-fold cross-validation, and implemented using the kernel RBF. Empirical observations were considered to design the algorithm. Specifically, standing, lying, and using the elevator can be detected by evaluating the thresholds of the vertical acceleration (a_v), as well as the differential pressure (P_{diff}); (Decision Making I). We also observed that running exhibits high acceleration peaks similar to falling, which can result in misclassifications of these activities. Hence, the two cascade SVM classifiers aim to reduce such errors. When high peaks of acceleration are identified, priority is given to detecting a fall event, i.e., the first classifier (SVM-1) discriminates between a “possible fall” and “other activities-1.” In the latter case, the second classifier (SVM-2) is executed to distinguish walking from “other activities-2” (i.e., running and walking upstairs and downstairs). If “other activities-2” is recognized, the thresholding method “Decision Making II” classifies running, walking upstairs and downstairs, and possible falls. Finally, when a “possible fall” has been detected, the post-impact verification is conducted.

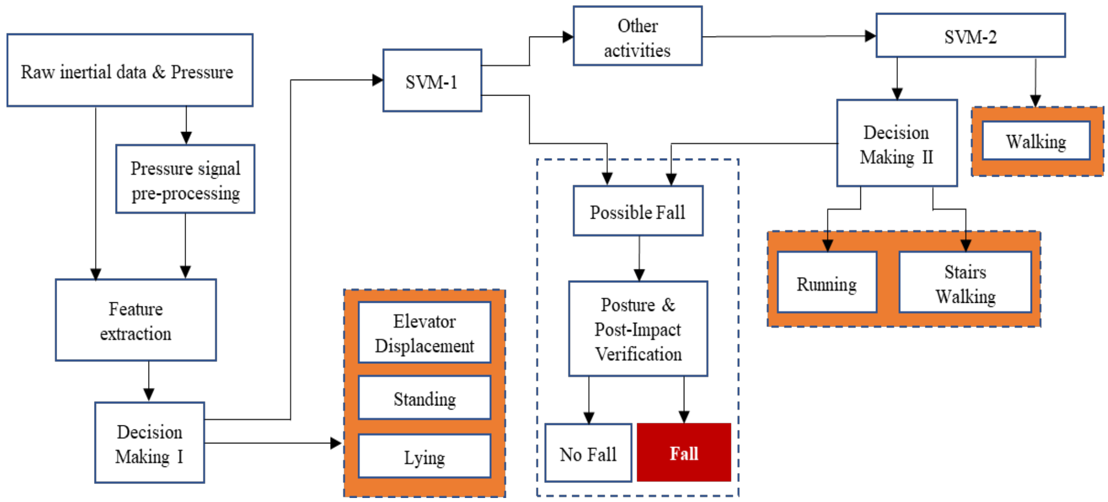


Figure 6. Algorithm to identify fall events and related motion activities prior-to and post the impact event.

Source: Authors' elaboration.

Decision making I and support vector machine I (SVM-1): this stage discriminates the activities that do not involve stepping, i.e., standing, lying, and using the elevator. To define a non-movement scenario, the threshold of the $var\ (a_{mag})$ should be less than $1m/s^2$. Lying and standing can be detected by evaluating the mean of the vertical acceleration (μ_{av}), whereas to determine if the user is riding an elevator, the threshold of (P_{diff}) is >7.5Pa/s (see Figure **7**). In case of movement, i.e., $var\ (a_x) > 1m/s^2$, the first classifier is executed (SVM-1). The inputs of SVM-1 are the minimum and the maximum of (ω_y), and the $var\ (a_{mag})$, whereas the outputs are "possible fall" and "other activities-1." When the former is identified, the "Posture Verification" process takes place. Specifically, a fall is detected when the user remains motionless for at least 10 seconds without changing their posture.

Decision making II and support vector machine 2 (SVM-2): this stage recognizes motion activities that involve stepping, i.e., walking, running, and walking upstairs and downstairs, as well as to detect possible falls (see Figure **8**). More specifically, SVM-2, whose inputs are $var\ (a_{mag})$, and $var\ (a_x)$, discriminates between walking and "other activities-2." When SVM-2 detects other activities, the "Decision making II" process is executed. Decision-making II recognizes running, upstairs and downstairs, and possible falls. Empirical knowledge is leveraged by applying thresholding to P_{diff}, and μ_{av}. For instance, according to our observations, in the walking-stairs activity, the vertical displacement could be distinguished when P_{diff} is over 4 kPa/s. If P_{diff} is positive, the user is descending the stairs; otherwise, the user is ascending. As in the previous stage, the posture verification process is also executed.

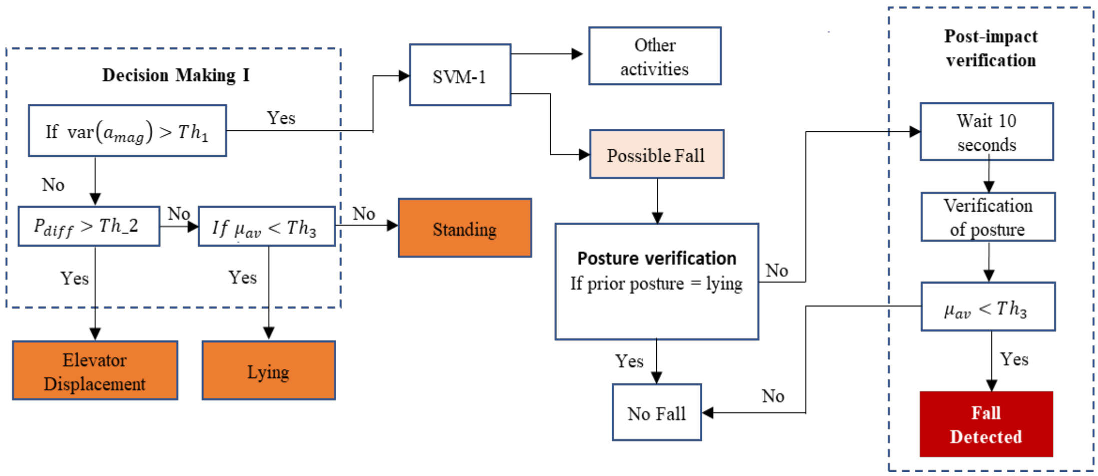


Figure 7. Scheme of the recognition of non-motion activities using thresholding and possible falls using the classifier SVM-1.

Source: Authors' elaboration.

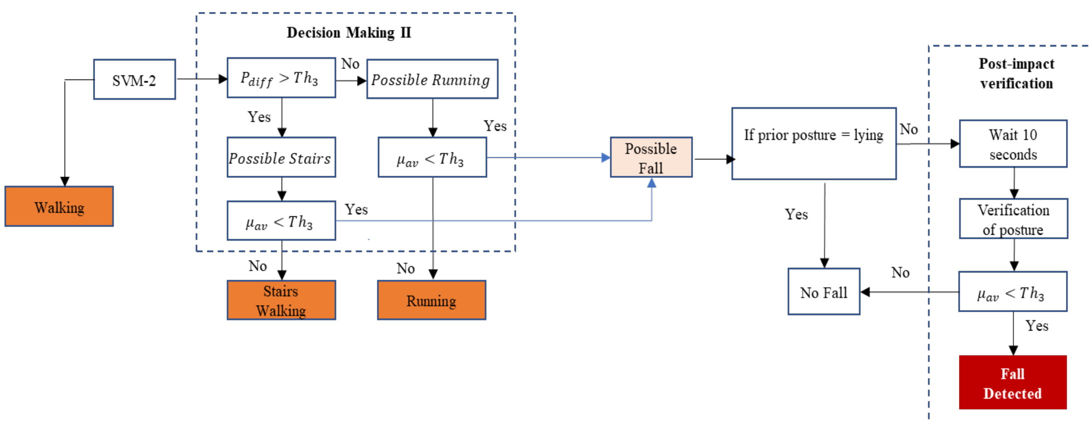


Figure 8. Scheme of the recognition of motion activities using thresholding and possible falls using the classifier SVM-2.

Source: Authors' elaboration.

Evaluation

The assessment of the performance of the classifiers was conducted in terms of sensitivity, specificity, and accuracy, as follows:

$$Sensitivity = \frac{TP}{TP + FN} \times 100 \tag{1}$$

$$Specificty = \frac{TN}{TN + FP} \times 100 \tag{2}$$

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \times 100 \tag{3}$$

where TP is the number of the instances correctly classified as "possible fall" (SVM-1) or walking (SMV-2); TN, is the number of instances correctly classified as "other activities-1" or "other activities-2" by SVM-1 or SMV-2, respectively; FP corresponds to the number of instances incorrectly classified as "possible fall"' or walking; and FN is the number of instances incorrectly classified as "other activities-1" or "other activities-2," by SVM-1 or SMV-2, respectively. The performance of the entire algorithm was evaluated by calculating the hit rate of the recognition for each activity.

RESULTS

Offline results: The confusion matrix of SVM-1 indicates a low performance of this classifier with an approximate 50 % of misclassifications of "possible fall," whereas "other activities-1" (see Table **1**) presented a good rate of correct classifications. By contrast, the confusion matrix of SVM-2 indicates a good performance for both instances. Namely, 192 "walking" and 184 "other activities-2" instances were correctly identified, whereas 15 "possible fall" and 14 "other activities-2" were misclassified (see table **2**). As seen in Table **3**, SVM-1 exhibited low performance regarding sensitivity (77.41 %) and specificity (78.86 %).

Table 1. Confusion matrix of the SVM-1 classifier.

		Recognized	
		Possible Fall	Other activities-1
Expected	Possible Fall	48	14
	Other activities-1	41	153

Table 2. Confusion matrix of the SVM-2 classifier.

		Recognized	
		Walking	Running/Stairs
Expected	Walking	192	15
	Other activities-2	14	184

Table 3. Offline recognition performance of the classifiers SVM-1 and SVM-2.

Output	**Accuracy(%)**	**Sensitivity(%)**	**Specificity (%)**
Possible Fall – Other activities -1	89.21	77.41	78.86
Walking – Other activities -2	90.59	92.75	92.92

During the offline testing, a routine was created by concatenating data collected in the offline protocol, including falls, elevator displacement, and activities such as standing, walking, running, and walking upstairs and downstairs. Figure **9** illustrates an example of this routine, showcasing the recognition activities and the vertical acceleration patterns associated with each activity. This sequence of events was obtained by randomly concatenating the activities to test the algorithm's ability to adapt to sudden changes between them. Specifically, the signal represented the activities of study separated by signal blocks with the following sequence: standing, walking, walking upstairs or downstairs, running, riding an elevator, and falls. As expected,the magnitude of the acceleration while walking is low compared to running or walking upstairs or downstairs. It can also be observed that falls can have similar peak values to running, although they last for a very short time.

The performance of the entire algorithm was assessed by calculating the hit-rate percentage, as indicated in Table **4**. Walking, standing, riding the elevator, and falls did not exhibit misclassifications. The 15 % of misidentifications of the walking upstairs and downstairs activity might be caused by the body movement changes during ascent and descent stairs, which could impact the selected thresholds of the P_{diff}. Nonetheless, the performance of the algorithm indicates that using thresholding in combination with cascade SVM is a robust method with, not misclassifications of falls.

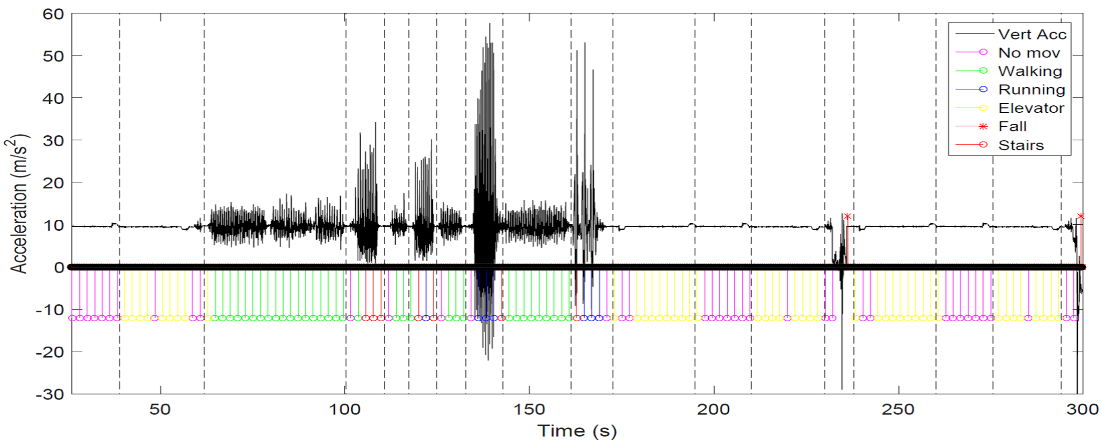


Figure 9. Offline activity recognition and fall detection based on vertical acceleration. This includes elevator displacement, standing, walking, running, using the stairs, and fall events.

Source: Authors' elaboration.

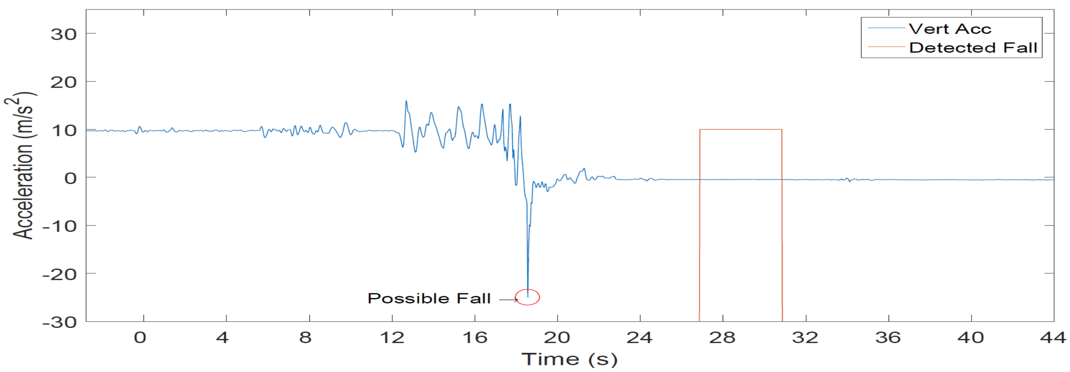
Table 4. Hit rate for the activity recognition and fall detection algorithm (offline)

Activity	**Hit rate (%)**
Lying	100
Standing	100
Elevator	100
Walking	96.60
Running	92
Walking-Stairs	85
Fall	100
Algorithm	96

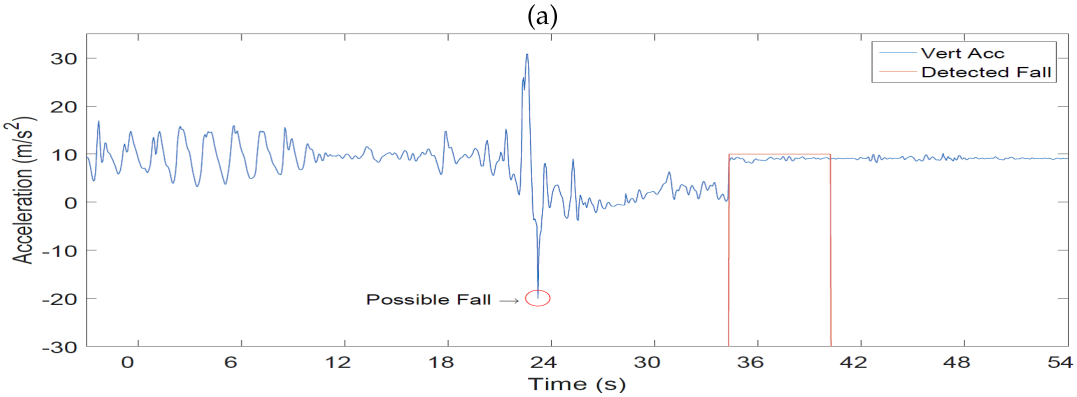
Source: Authors elaboration.

Real-time results: Various tests were conducted by five participants: two participants took part in the training stage, whereas three new participants carried out the real-time protocol. Thus, we were able to assess the performance of the algorithm with a new group of subjects. We considered real-world scenarios such as the fall recognition examples illustrated in Figure **10**. In the first case (see Figure

10a), the user falls (the vertical acceleration achieved a value of $20\ m/s^2$) after performing a short walk; and then, he lies on the ground (the vertical acceleration was approximately equal to $0\ m/s^2$). The system detects a fall after the verification process. It confirms that the person did not change its body position after a while, i.e., the person remained on the floor. In the second example (see Figure **10**b), the user walks, then stops for a few seconds, and falls (t = 24 s); since the subject remained still, the fall was detected.



(a)



(b)

Figure 10. a) Fall detection in real time while the user was walking. b) Fall detection after the user made a short stop during a walk tries to recover and remains still.

Source: Authors elaboration

The algorithm can identify the pattern of falls and contextualize the events according to the thresholding methods. Interestingly, falls of all participants were correctly classified (see table **5**, which shows the potential of the algorithm in real-time.

Table 5. Hit rate for the activity recognition and fall detection algorithm (Real-Time).

Activity	**Hit rate (%)**
Lying	100
Standing	100
Elevator	100
Walking	91
Running	87.5
Walking-Stairs	76.5
Fall	100
Algorithm	91

Source: Authors elaboration

The performance of the algorithm in real-time was lower than the performance obtained offline, as shown in Table **4** and Table **5**. The hit rate of the activity recognition decreased when performing movement activities, i.e., walking (from 96.60 % to 91 %), running (from 92 % to 87.5 %), and using the stairs (from 85 % to 76.5 %), which can be the most challenging movement. These results are consistent since a new group of participants also conducted real-time testing. Moreover, the algorithm's performance might be affected by additional factors, including participants' speed during the tests, or environmental changes. Despite these aspects, the algorithm was able to correctly recognize in real-time the "no-movement activities" (see Table **5**), while there were no falls' misrecognitions. Conversely, walking upstairs and downstairs remained challenging with a hit rate of detection of around 23 %. The main limitations of the present study include that the results were obtained from a small data set, tests were conducted with young subjects in controlled conditions, and only forward falls were studied. However, the results are promising considering that real-time tests were conducted with subjects who did not participate in the training tests.

CONCLUSION

This paper presented a real-time algorithm for fall detection, which contextualizes fall events by recognizing the activities performed before and after the incident. These activities were determined using a wearable inertial measurement unit and a barometric sensor. The algorithm combined thresholding and SVMs, which allowed for extending its functionality to any user without prior training. We defined a three-stage detection method based on motion activities recognition to increase the algorithm's robustness. Namely, the user's previous and subsequent activity are analyzed when detecting a possible fall alarm. By doing this, it is only necessary to store information about the most recent previous activity, making the memory requirement very low. As such, the algorithm did not exhibit misclassifications of falls in the real-time performance tests, whereas the activity recognition achieved a hit rate equal to 91 %. Future research should include validating the proposed algorithm with vulnerable populations in natural conditions, modeling various types of falls, and comparing it with other machine learning techniques.

FUNDING

This research was partly funded by the Colombian Administrative Department of Science, Technology, and Innovation (COLCIENCIAS) and the Universidad Industrial de Santander (UIS), grant FP44842-507-2014, project 1817; and the Universidad El Bosque, grant PCI2019-10784.

ACKNOWLEDGMENTS

The authors are thankful to participants, Juan Camilo Bravo, and the students of the CEMOS group at the Universidad Industrial de Santander.

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