LifeSeniorProfile: A Multisensor Dataset for Elderly Real-time Activity Track

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Abstract: Real-time tracking and detection of risky situations in the elderly, such as falls and sudden changes in vital signs, requires reliable, continuous, and automated monitoring systems based on relevant information. Wireless biosensors provide a great opportunity to remotely detect and monitor hazardous situations, allowing for a fast response in an emergency. Motion data is widely used to track daily activities. Physiological data can also be used for this exact purpose. However, there is yet to be a database available in the field of research in which the patient's physiological and movement information were collected simultaneously, considering daily activities and simulation of falls. This work presents a multisensor dataset for developing real-time tracking systems for the daily activities of older people. The data sensed refer to movement, using a triaxial accelerometer, and physiology, considering blood volume pulse, electrodermal activity, heart rate, inter-beat interval, and skin temperature. We collected these data from ten volunteers while performing 36 daily activities in a simulated environment.

1 INTRODUCTION

Monitoring, detecting, and classifying activities of older people through non-invasive wearable systems is an open research area due to the similarity between movement data sensed in daily activities and risky situations, such as falls. Recently, many machine learning algorithms, especially those that explore deep layers of neural networks (Mauldin et al., 2018) (Li et al., 2019) (Santos et al., 2019), have tried to search for hidden details of motion data of accelerometers, gyroscopes, barometers, and magnetometers to identify features that classical algorithms cannot identify. Despite the promising results, even these high-performance algorithms hardly reveal a real risk, achieving a false positive rate close to zero.

Accelerometers are the most common motion sensors used to identify human activities, providing real-time relative acceleration in a given direction, which varies according to available freedom degrees. In the rest state, the accelerometers share quasi-static values, and at excessive motion, they provide an acceleration peak. This behavior is adequate to develop a low-precision algorithm based on peak detection signals to detect fall situations and identify elderly risk situations. On the one hand, this algorithm is ineffective since many risk-free activities also have the same data signature. On the other hand, the foundation is the same for many fall detection systems developed in various research. Over the years, many studies have tried to improve these results by adding different motion sensors, but this problem is still an open research area.

Our primary motivation for this work is based on the direct correlation between accidental falls and vital signs (Naschitz and Rosner, 2007); this correlation is not explored in most of the research data available to develop systems that explore risk situations for older people. Integrating vital signs with motion signals offers a considerable advantage for identifying, detecting, and classifying daily activities and fall risks. However, this integration is rarely addressed in the available works (Oliver and Healy, 2009) (Vas-

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sallo et al., 2009).

This work provides a dataset of multisensory information, which includes, in addition to traditional motion sensors, some physiological sensors collected during activities of daily living and risky situations. We designed this database to analyze changes in vital signs caused by daily activities and falls. These data enable us to explore the fusion of physiological and motion data and classify all sensors based on their importance in detecting daily activities and falls, allowing us to give weight to each element sensed.

2 RELATED WORK

This section describes articles encompassing datasets of wearable sensors employed to predict falls and daily activities, and Table 1 emphasizes the main points of the related articles concerning the work presented here. Table 1 lets us notice the main similarities and differences between this work and the others for comparison and elaboration of some conclusions.

The first comparison in the table can be made by evaluating the position of the sensors on the participants' bodies. While some related works seek to use several sensors in different body positions, like (Casilari et al., 2017) and (Saleh et al., 2021a), the LifeSenior dataset seeks to use a single device located on the participants' wrists, which is the same strategy used by (Garcia-Ceja et al., 2021) and (Bruno et al., 2014) datasets. This strategy is based on the idea that the wrist is a well-accepted place to create products that can be used daily.

Another interesting point is related to the activities identified in each dataset. Related works that bring daily activities simulate them starting with a lack of movement and then the activity to be considered. Differently from that, the LifeSenior dataset brings the idea of executing a specific activity/risk situation to perform some daily activity/fall. The closest to this approach is found in the (Saleh et al., 2021a) dataset, where the fall activities are related to a previous daily activity, which leads to the fall.

The LifeSenior dataset contains data for 36 daily activities, including fall situations, which is the higher number of activity and fall data in a single dataset compared to related work. The closest to this quantity is the sheer number of fall types found in the FallAllD (Saleh et al., 2021a) dataset, the diversity of daily activities brought in HMP (Bruno et al., 2014), and even the fusion of falls and activities brought in UMAFall dataset (Casilari et al., 2017).

Regarding the sensors used, most of the related works use the accelerometer as the only or one of the motion sensors, which is the same approach as the LifeSenior dataset. Despite this, while (Saleh et al., 2021a) and (Casilari et al., 2017) rely on commonly used sensors such as the gyroscope and magnetometer and the smartphone that appears in some cases, the dataset proposed in this work is based on a few different sensors: PPG, EDA and Skin Temperature. These sensors are located in the same body position, the wrist, and can bring information that was previously little considered or unknown in other works. In addition, the authors believe that using data fusion from these sensors can bring new and unexpected results in future work.

3 SENSORS

We developed this dataset to record natural and provoked human actions, such as a fall, using several sensors that enable us to gather information from multiple points of view about each human action. We planned to include a triaxial accelerometer to detect human movement and insert sensors of temperature, electrodermal activity (EDA), and photoplethysmography (PPG) to extract vital signs.

3.1 Motion Sensors

All datasets evaluated presented data on daily activities and falls collected through motion sensors, primarily accelerometers. The main reason to focus on motion sensors is that most activities usually vary significantly in the sensing signal. For example, a fall is registered by a sequence of peaks and valleys in an accelerometer signal.

An accelerometer is an electromechanical device that measures the change in velocity over time (Piccinno et al., 2019). Acceleration measurements can be static, such as the force of gravity, or dynamic, caused by motion. In general, accelerometers translate an external acceleration signal into a displacement of their moving mass, called inertial mass. An accelerometer reports a drop as an abrupt change in values, represented by peaks and valleys (Bourke et al., 2007); a graph generated by an accelerometer during a fall shows the pre-fall, critical, and post-fall phases. Within the critical phase, it is still possible to identify the free fall, impact, and adjustment (Saleh et al., 2021b).

On the one hand, the presence of a high peak of acceleration followed by inactivity is a solid indicator to detect falls; on the other hand, more information is needed to avoid false alarms. For example, lying on a bed satisfy this accelerator sequence, making a

Table 1: Comparisons between the related articles and our work.

Dataset	Participants	Sensors	Sensors body position	Year	Activities
FallAllD	15	1, 2, 3	Neck, Wrist, Waist	2021	a
HTAD	3	1, 5	Wrist	2020	b, c, d, e, f, g, h
ShimFall&ADL	35	1	Chest	2020	a, i, j, k, l, m
HMP	16	1	Wrist	2014	e, l, m, n, r, s, t, u, v, w, x
UMAFall	17	1, 2, 3, 4	Ankle, Waist, Wrist, Chest	2017	a, k, l, m, n, p, q, r
LifeSenior	10	1, 5, 6, 7	Wrist	2022	a, l, m, o, r, y, z

Sensors: 1 - Accelerometer, 2 - Gyroscope, 3 - Magnetometer, 4 - Smartphone, 5 - PPG, 6 - EDA, 7 - Skin temperature.
Activities: a - Fall, b - Mop floor, c - Sweep the floor, d - Type on a computer keyboard, e - Brush teeth, f - Wash hands, g - Eat chips, h - Watch TV, i - Jumping, j - Lying Down, k - Bending/Picking up, l - Sitting/Standing to/from a chair, m - Walking, n - Climbing Stairs Down/Up, o - Loss of Motor Balance, p - Hopping, q - Light Jogging, r - Lying down (and getting up) on (from) a bed, s - Comb hair, t - Drink from a glass, u - Eat with fork and knife, v - Eat with a spoon, w - Pour water in a glass, x - Use telephone, y - Standing, z - Crouching and coming back

fall detection system with exclusive use of this approach somewhat limited. Therefore, we structured this dataset by collecting vital signs to analyze how this information can compose with motion information to decide about a daily activity or a fall.

3.2 Vital Signs Sensors

The temperature sensor enables us to identify body changes that may indicate simple disorders, such as a fever crisis, or more severe disorders that can compromise the functioning of vital organs. If the body temperature exceeds 42ºC, the individual is at risk of dying, as well as when the measured body temperature drops below 30ºC (Holtzclaw, 1993). The temperature sensor, combined with a motion sensor, can help to identify the cause of a fall or fainting.

Electrodermal activity (EDA) is the term used to define autonomous changes in the electrical properties of the skin. For this reason, the EDA sensor works by identifying electrical changes on the surface of the skin, allowing the monitoring of episodes of stress, anxiety, and the neurological state of an individual since it is much more susceptible to human emotions than just the analysis of heart rate (Blain et al., 2008).

The photoplethysmography (PPG) sensor uses an optical technique to identify blood volume changes in the microvascular tissue bed under the skin due to the pulsatile nature of the circulatory system (Kamal et al., 1989). The sensor system consists of a light source and a detector with a red and infrared light-emitting diode (LED). The PPG sensor monitors light intensity changes through reflection or tissue transmission (Tamura et al., 2014). Studies report that through PPG, it is possible to non-invasively estimate signals such as Electrocardiogram (ECG), heart pulse rate, saturation (Kamal et al., 1989), respiratory rate (Jarchi et al., 2018), and blood pressure (Kurylyak et al., 2013).

4 DATASET

LifeSeniorProfile was developed to contribute to world research in risk situation detection in older people based on wearable device solutions. Some datasets are available for research in this area, but almost all are based only on motion sensors. We propose a novel approach bringing up important vital signs correlated with motion data during simulated daily living activities and risk situations. We use the E4 wristband from Empatica (McCarthy et al., 2016), a medical-grade and trustworthy device that provides accurate real-time signals. Figure 1 displays the device with its sensors.

Figure 1: Front and back view of Empatica E4 device biosensor (McCarthy et al., 2016).

In addition to the pioneering nature of the proposed dataset in correlating vital signs with motion sensors, the proposal to use a device that is already widely clinically validated for use in research and is also certified by several regulatory agencies in the health area makes LifeSeniorProfile dataset unique.

4.1 Data Collection Process

Once the ethics committee of Group Conceição Hospital approved our experimental protocol (number 5,431,965), we started to recruit volunteers that fit the eligibility criteria. All the volunteers were recruited around the research laboratory; the recruiter explained all the study details to the volunteers before accepting them to participate.

The volunteers placed a bracelet (collection device) on the right pulse to collect and identify the vital and motion signs. The movement characterization and performance were accompanied by a physical therapist who recorded the movement type for each volunteer in each situation. These records, from the physical therapist and the collection device, known as the gold standard, are collected to be confronted later and related to the clinical variables of each research subject.

All movements were performed in an area covered by 50cm x 50cm and 20mm thick EVA plates to absorb impacts and avoid discomfort. For the fall simulations, a mattress with a fall area of 3m x 2m and 30cm thick was additionally positioned.

The movement simulation step involves executing a previous dynamic gait, successively followed by the unbalance or fall movement. The following dynamic gaits were simulated prior to each specific movement:

- Walking on a level surface at normal speed for 6 meters;
- Gait with vertical head movements; Up - Down - Forward;
- Walk around the obstacle in the format of an eight;

The study volunteers performed dynamic gait prior to all movement simulations to be collected and evaluated, including the performance of activities of daily living (ADL), simulations of different causes of imbalance, and simulations of different falls (Figure 2). These movements, which are described below, were used in previous studies of drop detector wearables to collect fall, non-fall, and near-fall signals (Bourke and Lyons, 2008) (Aziz and Robinovitch, 2011):

Activity Daily Living

- Stopped - without movement;
- Walking straight for 10 meters;
- Standing up and sitting in the chair - Perform the entire movement of sitting on a seat approximately 50cm high, wait 30 seconds and get up from the seat and stand up straight again;
- Squatting and coming back - Starting from the upright posture, the volunteer performs the squatting movement until he/she rests on the heels, waits 30 seconds, and returns to the standing position;
- Lying down and getting up - the volunteer performs the complete lying down movement with the face-up on a bed approximately 40cm high, waits 30 seconds, and gets out of bed, getting erect again.

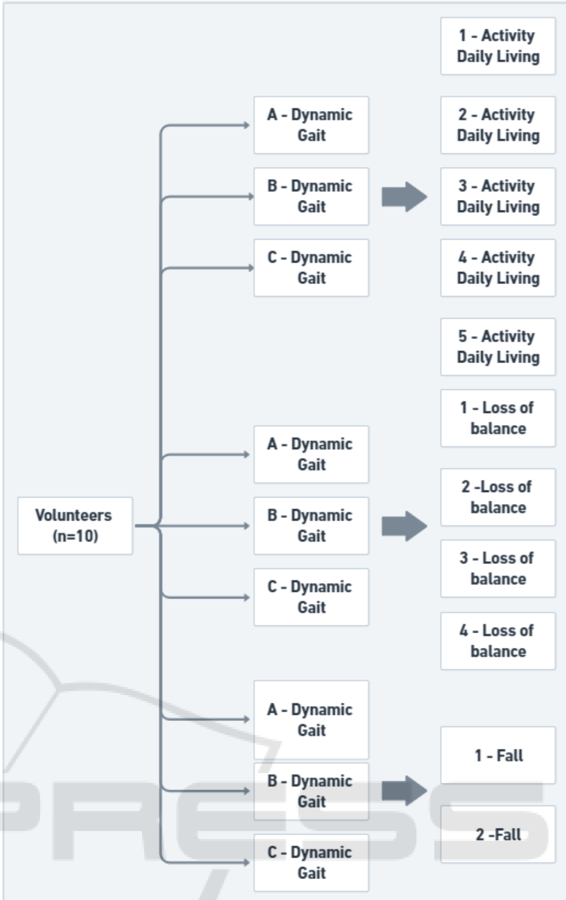

Figure 2: Simulations of different causes of imbalance and simulations of different falls.

Loss of Balance

- Sitting and Standing - the volunteer completes the entire movement of sitting on a seat approximately 50cm high, waits 30 seconds, and when standing up, simulates the loss of balance forward and finishes the erect movement;
- Standing and sitting - the volunteer performs the movement of sitting on a seat approximately 50cm high, simulating loss of balance due to incorrect weight transfer to the seat and ending the movement erect;
- Changing direction - Being initially stopped, perform a 180° change of direction and, in the end, simulate the loss of balance to the side and finish the erect movement;
- Reaching Object - Being initially stationary, the volunteer moves to look for an object on the

ground and, in the end, simulates the loss of forward balance and finishes the upright movement.

Fall

- Obstacle - Initially walking, the volunteer simulates limb collision with an obstacle (10 cm x 15cm bulkhead) and then simulates the fall movement on the mattress;
- Cadence continuity - Initially walking, the volunteer simulates the forward slip and then simulates the movement of falling on the mattress;
- Syncope - Initially stopped, relax lower limbs to simulate a fall on a mattress.

These movements were captured by the device instrumentation, generating reference signals associated with these movement patterns, which allow training and validate different models of algorithms capable of characterizing movements and detecting falls.

4.2 Eligibility Criteria (Ethics Committee)

Volunteers were selected following ethical principles and with comprehensive selection criteria. Volunteers are adults, without gender restriction, over 18 years of age, and in total health; that is, volunteers who presented at least one of the following characteristics were considered unfit for the study: (i) neurological diseases; (ii) gait disorders and musculoskeletal diseases; (iii) uncorrected visual impairment; (iv) inability to maintain orthostatism; (v) need and assistance to get around; (vi) functional dependency; and (vii) recent orthopedic trauma.

4.3 Characteristics of the Participants

The dataset consists of data from 10 volunteers with an average age of 36 years; all of them meet the criteria established in the 4.2 section, 60% male with average weight and height of 85kg and 1.74m, respectively. Regarding female volunteers, the average weight and height were 72kg and 1.65m. Further information about the volunteers was preserved for confidentiality reasons provided in the consent form for participation in the research.

4.4 Experimental Protocol

We divided the experimental protocol into three groups that simulate Daily Living Activities (DLA), Loss of Motor Balance (LMB), and Effective Fall (EF). In order to standardize the beginning of data collection, we created three dynamic gaits: (i) on a flat surface at normal speed for 6 meters, (ii) with vertical head movements, and (iii) walking around an obstacle in the shape of an 8. After performing these marches for 30s, the collection of movements in the database was started, as detailed in Table 2.

Altogether, we obtained 360 records identified with the number of each individual, followed by the initial simulation applied in the test, the type of gait, and the effective simulation, according to the last column of Table 2.

4.4.1 Effect of Data Merging for Some Activities

The data collected by the E4 wristband is transmitted to the Empatica platform and exported in CSV (Comma-separated values) files to be manipulated in spreadsheet and graphics software.

The sensors record data at different rates:

- Accelerometer - 32 points per second;
- PPG sensor - 64 points per second for blood volume and 1 point per second for heart rate;
- EDA sensor - 4 points per second;
- Temperature sensor - 4 points per second.

To analyze the inter-sensor correlation, we upsampled the sensors with lower frequencies, using the linear interpolation method to normalize all data to 64Hz (the highest frequency found among the sensors).

We used the accelerometer as a base sensor to identify a volunteer's movement, daily activities, loss of balance, and fall. We looked for variations that occurred in the other sensors at the points where the events were identified on the accelerometer graph. We noticed that the Blood Volume Parameter (BVP) showed a strong correlation with the events recorded by the accelerometer, as can be seen in Figure 3, which shows the daily activity record, with gait and vertical movements with the head, and getting up and sitting down from the chair.

In this same record, when analyzing the normalized data of heart rate, temperature, and electrodermal activity, large variations are not highlighted, either null or very small, as shown in Figure 4. However, it is not possible to say that these signals are not influenced by the movement of the volunteer, as it is necessary to consider that they have a lower frequency of records. What can be seen in Figure 4 is that the Heart Rate (HR) has its records interrupted before the end of the collection at the 6000 points of the graph.

These same characteristics, peaks in the accelerometer and the synchronized blood volume signals, could be observed in the records of loss of balance activities and falls.

Table 2: Details of the movements present in the database.

Simulation	Dynamic gait (30s)	Movement simulation	Time	File name
DLA	A, D e G	1	10s	V1_DLA_A_1, V1_DLA_D_1, V1_DLA_G_1
		2	The necessary	V1_DLA_A_2, V1_DLA_D_2, V1_DLA_G_2
		3	2 repetitions	V1_DLA_A_3, V1_DLA_D_3, V1_DLA_G_3
		4	2 repetitions	V1_DLA_A_4, V1_DLA_D_4, V1_DLA_G_4
		5	2 repetitions	V1_DLA_A_5, V1_DLA_D_5, V1_DLA_G_5
LMB		6	The necessary	V1_LMB_A_6, V1_LMB_D_6, V1_LMB_G_6
		7		V1_LMB_A_7, V1_LMB_D_7, V1_DLA_G_7
		8		V1_DLA_A_8, V1_DLA_D_8, V1_DLA_G_8
		9		V1_LMB_A_9, V1_LMB_D_9, V1_LMB_G_9
EF		10		V1_EF_A_10, V1_EF_D_10, V1_EF_G_10
		11		V1_EF_A_11, V1_EF_D_11, V1_EF_G_11
		12		V1_EF_A_12, V1_EF_D_12, V1_EF_G_12

Simulation: DLA - Daily Living Activities, LMB - Loss of Motor Balance, EF - Effective Fall
Dynamic Walking: A - Walking on a flat surface at normal speed for 6 meters, D - Walking with vertical head movements: Up – Down – Forward, G – Walking around an obstacle in figure eight.
Motion simulation: 1 – Standing, 2 – Walking, 3 – Standing up and sitting in the chair, 4 – Crouching and coming back, 5 – Lying down and standing up, 6 – Sitting down and standing up, 7 – From standing and sitting, 8 – Changing direction, 9 – Reaching object, 10 – Obstacle, 11 – Cadence continuity, 12 – Syncope.

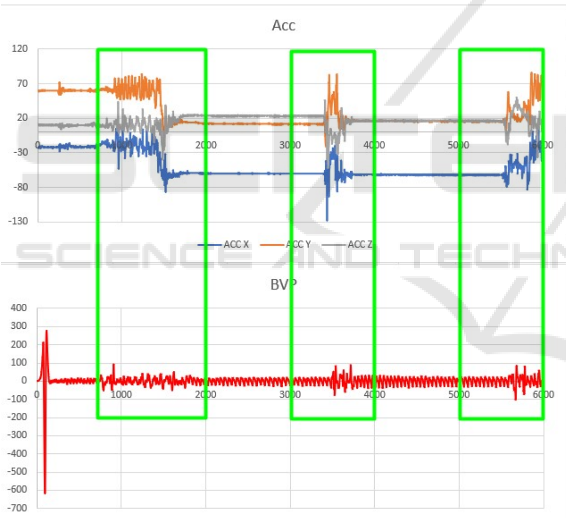

Figure 3: Accelerometer and PPG sensor signals.

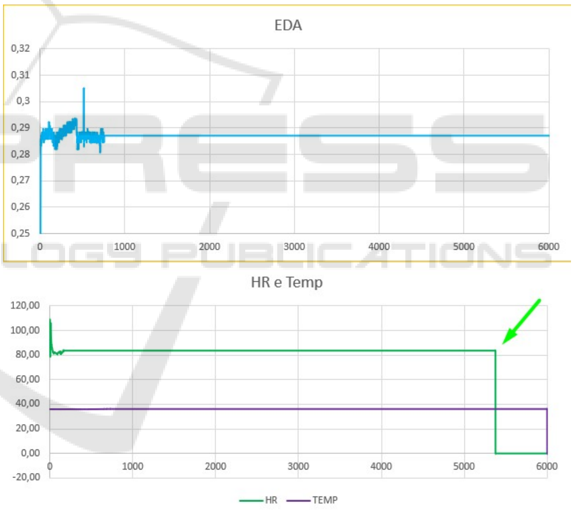

Figure 4: Signals from heart rate (PPG) and EDA and temperature sensors.

The data collection of the Empatica platform provides a graphical view of the data with native linear interpolation for data normalization. This facility enables us to verify the influence of the volunteer's movement also on the EDA and temperature sensors, as shown in Figure 5 - recording a gait simulation around obstacles in eight, followed by a fall simulating a syncope.

Figure 5 shows the last 10 seconds of the collection, where the accelerometer data are unified, with no significant variation. However, the EDA sensor and BVP variations are quite different. Nevertheless, the temperature undergoes a small drop that slightly changes the graphic.

Machine learning algorithms see data raw without the need for graphics. Thus, these slight variations in the sensors and the accelerometer serve as points of differentiation that can make a big difference in deciding whether an event can be classified as a fall or just a movement of an individual purposefully lowering himself, for example.

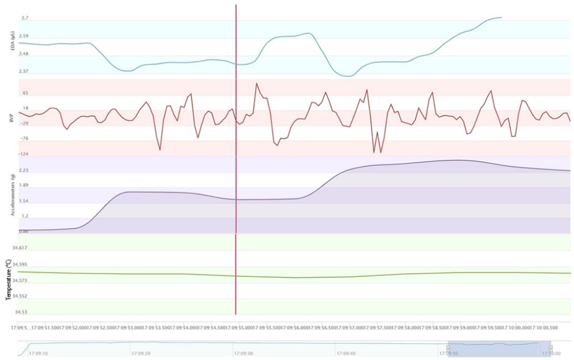

Figure 5: Signals of accelerometer, BVP, EDA, and temperature sensors.

4.5 Dataset Characteristics

Each LifeSeniorProfile dataset file encompasses a dynamic gait simulation followed by a motion simulation that can be a daily activity, loss of balance, or a fall. Preceding the movement simulation with a dynamic gait makes the collected data closer to a real event, where some previous situation of normality will always precede a specific movement situation. This procedure is another differential of the proposed model concerning those currently available.

We separated data according to the sensor used to perform the measurement; therefore, all participant files were unified and separated by the sensors in the wearable. To avoid losing the references present in each simulation and to allow the individual analysis of the curves, a “Label” file was created containing the information of the last column of the previous table. This process resulted in the following files:

- ACC-X.csv - Containing the accelerometer data referring to the X axis;
- ACC-Y.csv - Containing the accelerometer data referring to the Y axis;
- ACC-Z.csv - Containing the accelerometer data referring to the Z axis;
- BVP.csv - Containing blood volume pulse data;
- EDA.csv - Containing electrodermal activity data;
- HR.csv - Containing heart rate values;
- TEMP.csv - Containing temperature data;
- LABEL.csv - Containing the characteristics of the experimental protocol.

For convenience, the entire dataset was split into the train and test sets. Seven subjects were included in the train set and three in the test set. This procedure helps develop algorithms that use the training set to learn the characteristics, and the developed model is not seen as data (test set).

4.6 Dataset Limitations

This dataset has some limitations that need to be taken into consideration:

- Limited number of volunteers - as the number of volunteers performing the simulated movements is not higher than other datasets, the researcher needs to consider specific algorithms; some insights can be the product of a poor number of collections and not from the algorithm performance.
- Age of volunteers - the average age of volunteers is lower than that of the elderly, generating a loss of specific characteristics found only in older adults. This choice prevents older adults from getting injured, even with the falls being controlled and assisted by a medical team.

5 CONCLUSION

Different methods of detection and monitoring of daily activities performed by the human body have already been developed and explored by numerous scientific articles in the literature. Each method has its peculiarities, but there is a consensus that motion sensors are the ones that present the most acceptable result within a feasible scenario in wearable devices. Despite this good performance, these types of sensors also present a high rate of false positives, like detecting an activity that was not executed. This fact occurs due to the motion signal characteristics that can be easily confused with normal daily movements.

This article displays that the association of physiological sensors to the usual movement provides relevant information for reducing the number of false positive detections, given the evident correlation between the different behavior of the vital signs in a real detectable activity and a mistakenly detected one. This dataset enables the researchers to explore in detail the behavior associated with falls and daily living activities, thanks to a long time of data collection for each simulated movement and the context available; therefore, providing a way to consider not only the exact movement but also what occurred before and after it. Algorithms that consider movement context, like a fall, can find important information about the vital sign status before the fall, what the user was doing before the fall, and also how is the motion characteristics after the fall, enabling us to detect if it was senseless or moving.

Our proposed dataset is an essential new tool to improve the results of activity detector algorithms based on non-invasive wearable sensors. It is now available for new researchers and can be downloaded at https://github.com/lifeseniorproject/profile.

For future work, we plan to collect more data from users and include more older people, which was not included in this article due to the difficulty of recruiting them. Increasing this dataset enables us to use deep learning algorithms.

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