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UMAFall: A Multisensor Dataset for the Research on Automatic Fall Detection

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Abstract

The progress in the field of inertial sensor technology and the widespread popularity of personal electronics such as smartwatches or smartphones have prompted the research on wearable Fall Detection Systems (FDSs). In spite of the extensive literature on FDSs, an open issue is the definition of a common framework that allows a methodical and agreed evaluation of fall detection policies. In this regard, a key aspect is the lack of a public repository of movement datasets that can be employed by the researchers as a common reference to compare and assess their proposals.

This work describes UMAFall, a new dataset of movement traces acquired through the systematic emulation of a set of predefined ADLs (Activities of Daily Life) and falls. In opposition to other existing databases for FDSs, which only include the signals captured by one or two sensing points, the testbed deployed for the generation of UMAFall dataset incorporated five wearable sensing points, which were located on five different points of the body of the participants that developed the movements. As a consequence, the obtained data offer an interesting tool to investigate the importance of the sensor placement for the effectiveness of the detection decision in FDSs.

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Keywords: Fall detection systems, accelerometer, gyroscope, smartphone, dataset, wearable, sensors

1. Introduction

Falls constitute a leading cause of injuries among seniors and a major source of costs for national health systems as far as 28%–35% of the population over 64 suffer at least one fall per year [1,2]. Fall-induced morbidity and mortality have been shown to be closely correlated to the delay of the first aid treatment after the fall [3]. As a consequence, the design of trustworthy and low-priced automatic Fall Detection Systems (FDS) has become an important research topic during the last years. The noteworthy advances in the fields of sensor miniaturization, tracking systems,

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wireless communications and wearable electronics have fostered the emergence of many research works focused on deploying FDSs that can be seamlessly transported by the user to transmit an alarm (through a message, a voice call, etc.) in case that a fall is detected. The acceptance of personal devices that natively integrate accelerometers (such as smartphones, smartwatches or smartbands) has notably eased the application of FDS, which can be implemented as simple *apps* at almost no cost.

One key issue associated to the research on FDS is the assessment of the fall detection algorithms. FDSs can be regarded as binary decision systems aimed at discriminating movements associated to falls from those caused by ordinary Activities of Daily Living (or ADLs). Thus, the accuracy of a FDS is generally evaluated by estimating those metrics (sensitivity, specificity, precision, etc.) that are typically applied to pattern recognition systems with binary classification. To obtain those metrics, FDSs must undergo systematic tests with different types of falls and ADLs. Due to the inherent difficulties of monitoring actual falls (particularly those experienced by older adults), most studies on FDS utilize mimicked falls and ADLs as evaluation patterns. Except for some cases where mannequins are employed [4], these movements are conventionally executed by a small set of experimental subjects (normally, young or healthy adults) that emulate different predefined falls by plummeting on a padded mat or mattress. The imitation of planned falls on a cushioning material as a validation method for FDS has been discussed in papers works such as [5,6,7,8] or [9], as far as real-life unexpected accidents may cause a different behavior of the human body than that provoked by imitated falls. But the fact is that just some studies (such as that presented by Zhang in [10]) have tried to track actual elderly users in a realistic scenario for a long period of time.

In any case, a scientific consensus about the methodology that must be followed to evaluate FDS is far from having been achieved. In this regard, one of the most relevant facts that reveals the absence of a common evaluation benchmark is the lack of a public ‘reference’ repository of mobility traces (mimicked or real) that can be employed to compare the performance of the detection algorithms. In fact, most authors that propose a new technique for fall detection do not utilize the traces captured by other studies and generate their own samples (which are generally not later released for further use) to assess the precision of their proposals. In very few papers the experiments of other studies are replicated. In addition, the typology and number of physical activities that are emulated to produce the traces (as well the number of experimental users that execute the tests) arbitrarily vary from one study to another. Consequently, the algorithms existing in the literature are not compared under the same conditions.

Only a few works on FDSs have made their ‘clinical’ databases available. Table 1 presents the basic characteristics of most of those datasets, including the number of different types of ADLs and falls that were emulated, the number of samples of each type, the number of experimental subjects (females and males) that executed the movements, the number and position of the ‘sensing nodes’ (normally a smartphone or a sensor embedding an Inertial Measurement Unit –or IMU-) and the nature of the magnitudes that are sampled and stored in the traces, mainly triaxial accelerometer (A) signals, but in some cases, gyroscope signals and information about the body orientation too.

As it can be noted from the table, all these datasets just utilize one or, in some studies, two sensing nodes to characterize the human mobility. Furthermore, in most cases, the unique node is placed in a fixed position (e.g. a trouser pocket when a smartphone is employed). Thus, the impact of choosing a particular location to attach the sensor cannot be systematically analyzed.

Studies such as [11] have investigated the optimal location for stand-alone smartphone-based FDS concluding that placing the sensor in a pocket may clearly decrease the efficiency of the detection decision. Other research works [12] [13] have shown that the accuracy of a FDS can be improved if the decision is based on the measurements from more than one wearable sensors (e.g. a smartwatch and a smartphone) located on different parts of the body.

The optimal location of accelerometers for the detection of everyday activities has been largely investigated [14].The project described in [15] employed 4 sensors (integrating a triaxial accelerometer and a triaxial gyroscope) located in four positions (ankle, wrist, waist and chest) to create an interesting dataset that characterizes 13 activities performed by 19 participants. However, the scheduled activities did not include any type of fall.

The goal of this paper is to describe UMAFall, a public dataset that has been designed to study the importance of the placement of the sensors for the effectiveness of fall detection algorithms. For that purpose, the traces incorporate measurements of the mobility of ADLs and falls that are simultaneously captured by five wireless sensing nodes placed on five different positions.

Table 1. Basic characteristics of other public datasets of falls and ADLs.

Dataset & Institution	No. of types of emulated ADLs/Falls	No. of samples (ADLs/falls)	No. of subjects (F/M)	No. of sensing nodes	Positions of the sensors	Sensors per point
Cogent Labs (Coventry University, UK) [16]	8/6	1968 (1520/448)	42 (6/36)	2	Chest Thigh	A G
MobiFall Dataset (1st version) BMI Lab, Technological Educational Institute of Crete (Heraklion, Greece) [17]	9/4	630 (342/288)	24 (7/17)	1	Trouser pocket	A G O
MobiAct Dataset (2nd version) [18]	9/4	2526 (879/647)	57 (15/42)	1	Trouser pocket	
TST Fall detection dataset. Università Politecnica delle Marche (TST Group, Ancona, Italy) [19]	4/4	264 (132/132)	11 (n. i.)	2	Right wrist Waist	A
SINTEF ICT (Trondheim, Norway)[13]	7/12	117 (45/72)	2 (n. i.)	2	Waist wrist	A G
tFall EduQTech. Education, Quality and Technology. University of Zaragoza (Teruel, Spain) [8]	Real Life conditions/8	10909 (9883/1026)	10 (3/7)	1 or 2	Pocket, Hand bag	A
SisFall Dataset. SISTEMIC (Univ. Of Antioquia, Colombia) [20]	19/15	4505 (2707/1798)	38 (19/19)	2	Waist	A A, G
UR Fall Detection Dataset. Interdisciplinary Centre for Computational Modelling University of Rzeszow (Krakow, Poland) [21]	5/3	70 (40/30)	5 (0/5)	1	Near pelvis (waist)	A
UniMiB SHAR dataset. Department of Informatics, Systems and Communication (University of Milano, Milan, Italy) [22]	9/8	7013 (5314/1699)	30 (24/6)	1	Left or right trouser pocket	A
Graz University of Technology [23]	10/4	492 (74/418)	10 (n. i.)	1	Waist (belt bag)	A G

Note: A: Accelerometer, G: Gyroscope, O: Orientation measurements. F: Females, M: Males, n. i.: not indicated

2. Description of the testbed

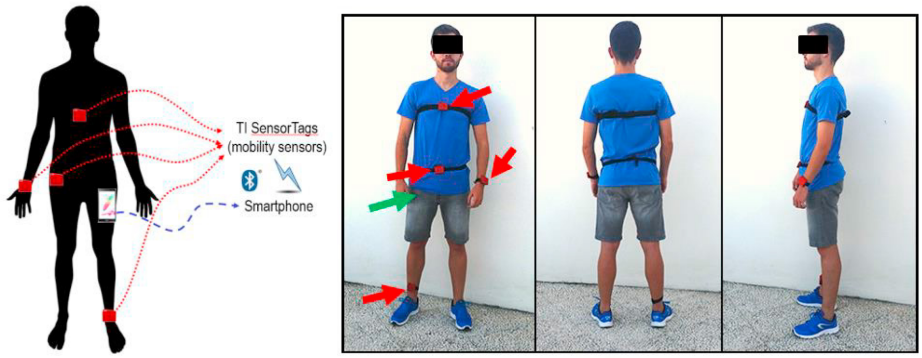
The utilized architecture to obtain the dataset is sketched in Fig 1(a). The system is based on the interaction between a smartphone and four wearable sensor motes located in four different positions of the body of the experimental users. The sensing units were implemented on four SimpleLink SensorTag units, produced by Texas Instruments[24]. These motes employ the CC2650 ARM microcontroller unit, which integrates a 2.4-GHz RF transceiver compatible with Bluetooth Low Energy (BLE) and IEEE 802.15.4 specifications. Thus, depending on the utilized firmware, diverse low-power wireless communications standards (Bluetooth Low Energy –or BLE-, ZigBee and 6LowPAN) can be supported. The nodes, which were conceived to ease the deployment of IoT (Internet-of-Things) networks, offer 10 embedded microelectromechanical (MEMS) sensors, comprising an InvenSense MPU-9250 multichip module. This motion tracking device consists of two dies combining a 3-axis gyroscope, 3-axis accelerometer and 3-axis magnetometer. Each SensorTag unit is typically powered by a CR2032 button cell lithium 3.0 V battery.

The central node in the system is an Android smartphone, which performs as a data sink. As most current smartphones are natively provided with a BLE interface, a BLE star topology of 5 nodes is deployed to interconnect the SensorTag units and the phone, which performs as the master of the BLE piconet.

The motes were programmed to periodically capture and send to the smartphone the measurements of the tri-axial mobility sensors (the x, y and z components of the acceleration, the angular velocity and Earth's magnetic field expressed in g's, °/s and µT, respectively) through the BLE connection. A specific Android *app* was in turn created and installed in the Smartphone to collect and save the data transmitted by the motes. The data are stored in a CSV (Comma Separated Values) formatted file. For every sample (consisting of the 9 magnitudes sensed by the motes), the smartphone adds a timestamp (referred to time the first sample was received) and the Bluetooth MAC address of the transmitting mote. Benefiting from the fact that smartphones also integrate an accelerometer, the app regularly activates this sensor and also saves in the CSV file the corresponding measurements of the accelerometer together with the other signals obtained from the Sensortag nodes. Thus, the smartphone is also employed to characterize the mobility of the experimental user.

The operation of the architecture is as follows: Whenever the *app* is initiated, the application interface requests the user to enter all the basic parameters which are required to identify the experiment. These parameters include the basic characteristics of the user profile: age, weight, height gender and name (users' names are anonymized and transformed into numerical IDs at a later 'post-processing' stage) as well as the typology of the activity (type of ADL or fall) that is going to be emulated by the experimental user. Since the same type of movement can be repeated by the same user, the trial number must be also provided. Besides, the *app* automatically detects the properties (number, nature, range, resolution, sampling rate and vendor) of the embedded sensors that are going to be employed by the nodes. All these data will be incorporated as a header at the beginning of the CSV log file.

Once that the experiment is described, the *app* informs the user that the scheduled movement can be executed. So, after clicking a 'start' button on the screen, a trace containing the measurements sampled by the five nodes is progressively saved in the log file. The capture ends when the user stops the app or after a pre-defined timeout (15s by default). After the monitoring phase is concluded, the trace file is saved in the internal storage of the smartphone with a file name that includes the subject identification, the typology of the executed movement and the date and time that the recording was initiated.



(a). Architecture (b) Picture of the sensor network

Fig. 1. Basic architecture of the system

3. Description of the traces

As it is illustrated in snapshot included in Fig.1(b) the SensorTag motes were attached with elastic straps to the ankle, waist, right wrist and chest (as it is indicated with red arrows in the figure). The smartphone is transported within the right trouser pocket (marked with a green arrow in the picture). This can be regarded as a 'natural' or 'ergonomic' placement for many smartphone users. These locations of the sensing devices (specially thigh, waist and chest) comprise those positions that are typically employed by the literature on FDS (see [25] [26] [27] or [28] for a state-of-the-art on this topic). The basic characteristics of the 17 users (10 males and 7 females) that participated in the experiments are described in Table 2.

Table 2. Personal features of the experimental subjects.

Feature	Range	Mean	Standard Deviation	Median
Age (years)	[18-55]	26.9	±10.2	24
Weight (kg)	[50-93]	69.9	±12.7	68
Height (cm)	[155-195]	171.5	±9.4	173

All the experiments were executed in a domestic environment (see pictures in Fig. 2), including a bedroom (A), a living room (B) and scales in an apartment block. Falls were mimicked on a mattress on a terrace.

All the recruited participants performed 8 different types of ADLs: 1) body bending (squatting), 2) climbing stairs down, 3) climbing stairs up, 4) hopping, 5) light jogging, 6) lying down (and getting up) on (from) a bed, 7)sitting down (and up) on (from) a chair, and 8) walking at a normal pace. Additionally, three different typologies of falls (1- backwards, 2- forwards, 3- lateral) were emulated by all the subjects (except by those two older than 50 years). For all the movements, the initial position of the body was standing straight up. Each participant replicated every movement at least 3 times.

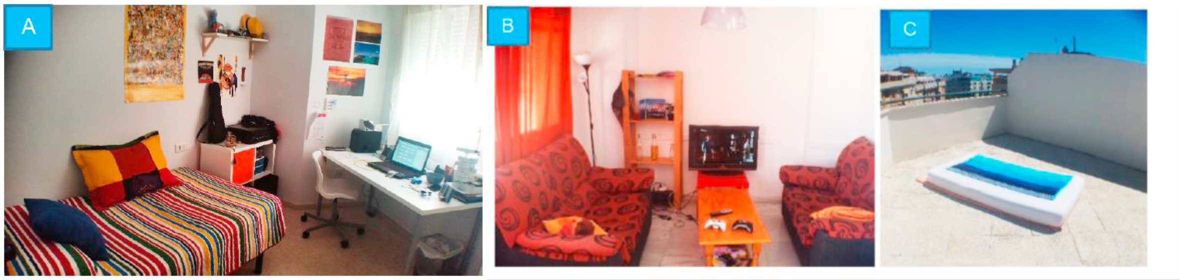


Fig. 2. Domestic environment where the experiments took place

The final obtained dataset includes 531 files (322 ADLs and 209 falls) stored in CSV format, which can be easily accessed and processed through a wide set of software environments, ranging from simple spreadsheet programs to high level mathematical analysis tools (such as Matlab). Every file includes the 15-second traces (measurements of the accelerometers, gyroscopes and magnetometer), captured by all the sensors during a single trial of a particular movement type. All the obtained traces are publicly available in [29] and [30]. The characteristics of the executed movements can be visualized in a set of videos which are also downloadable from the same Web page of the traces.

During the tests, two different smartphone models (Samsung S5 and LG G4) were employed. The models and characteristics of the built-in sensors of these Android devices and those of the Sensortag motes are presented in Table 3. The sampling rate for the accelerometer embedded in the smartphone was selected to the maximum value of 200 Hz. Due to the restrictions of the hardware in the motes and in order to avoid saturation of the Bluetooth communications, the sampling rate in the SensorTag nodes was set to 20 Hz.

Table 3. Range (resolution) of the sensors embedded in the sensing units.

Sensing unit	Sensors	Accelerometer	Gyroscope	Magnetometer
Samsung S5	*Invensense MPU-6500*	±2 g (16 bits)	Not employed	Not employed
LG G4	*LGE Accelerometer (BOSCH)*	±4 g (16 bits)	Not employed	Not employed
SensorTags	*Invensense MPU-9250*	±8 g (16 bits)	±256 º/s (16 bits)	±4800 μT (14 bits)

4. Basic analysis of the characteristics of the traces

Accelerometers measure at rest a value next to 1 g (an acceleration of 9.81 m/s^2) due to Earth's gravity. Thus, falls provoke the occurrence of unexpected peaks of the body acceleration, which are caused by the impact against the floor. Similarly, during a free fall, the accelerometer measurements rapidly decay to zero.

Threshold-based algorithms [25] offer a basic approximation to solve the problem of fall detection. Thus, these algorithms try to infer the existence of falls by constantly monitoring the evolution of the acceleration module, which is compared to one or several detection thresholds. The value of this module or SMV_i (Signal Magnitude Vector) for the i-th measurement of the accelerometer can be estimated as:

$$SMV_i = \sqrt{A_{xi}^2 + A_{yi}^2 + A_{zi}^2} \qquad (1)$$

where A_{xi}, A_{yi} and A_{zi} define the triaxial (x, y, and z) measured components of the acceleration vector.

As a first and elementary analysis of the UMAFall dataset, Fig. 3 shows the box-and-whisker plots of both the maximum and minimum values of SMV, which have been computed for all the movements of the same type and for the five employed sensors. On each box, the central line represents the median while the edges of the box indicate the 25th and 75th percentiles of each dataset. The whiskers in turn extend to the most extreme data points which are considered no to be not outliers while the outliers are individually plotted outside the interval as red dots.

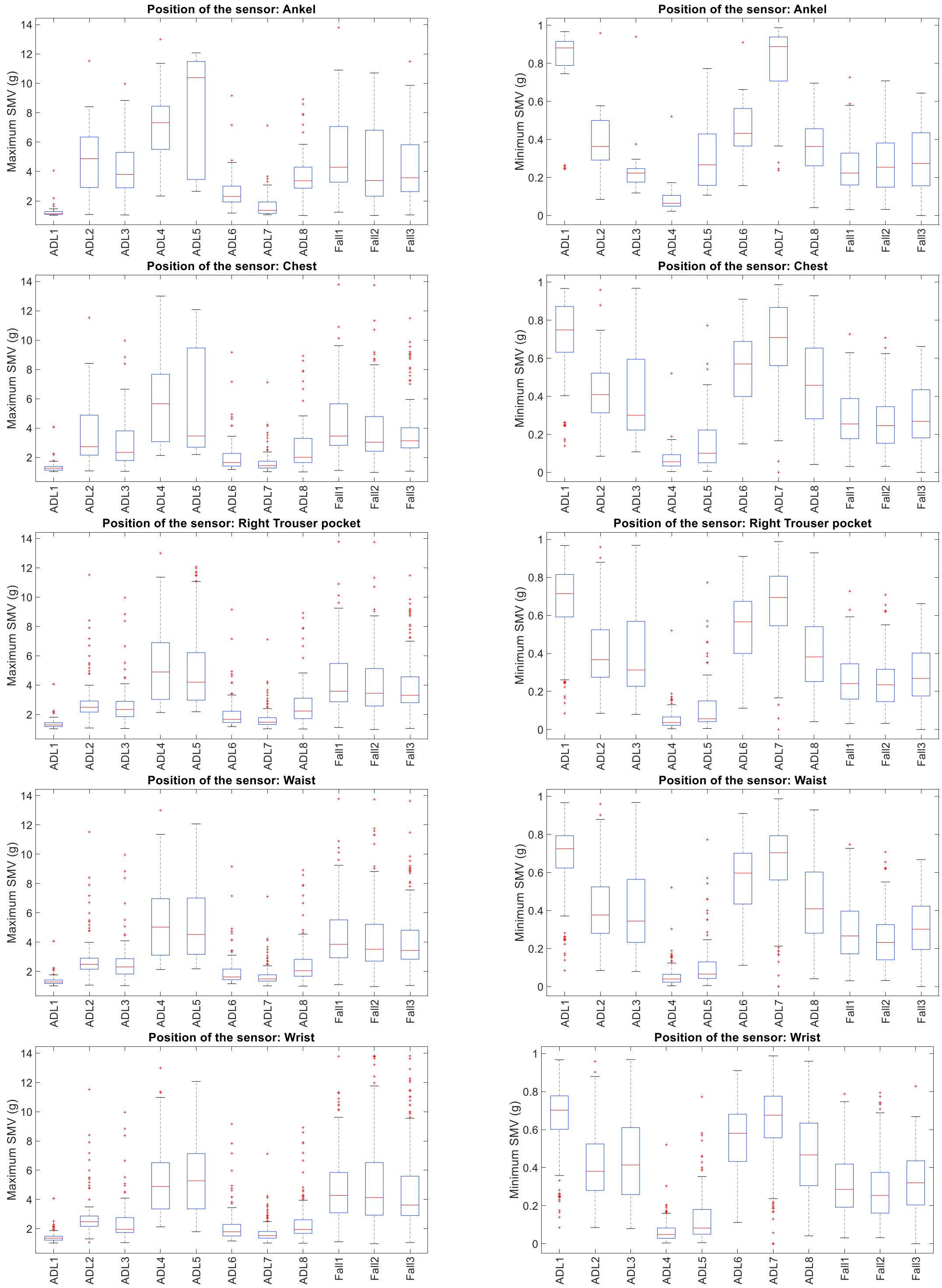


Fig. 3. Boxplots of the maximum and minimum acceleration magnitudes for the 11 considered different mobility patterns of ADLs (1; Squatting, 2: Go downstairs, 3: Go upstairs, 4: Hopping,5: Jogging,6: Lie down on a bed,7: Sit & get up from a chair, 8: Walking) and falls (1: Backward fall, 2: Forward fall, 3: Lateral fall)

The graphs illustrate the intrinsic difficulty of discriminating between falls from ADLS if just a simple 'thresholding' policy is considered. The box plots even show that certain physical activities (such as jogging or hopping, labelled as ADL4 and ADL5 in the figures, respectively) provoke higher mean peaks and decays of the SMV, than those induced by falls. From the figures we can also infer the inadequacy of the signals captured in certain positions (in particular the ankle) to perform the detection decision. With a sensor located in the ankle, even the peaks and 'valleys' in the acceleration module caused by a moderate activity such as walking could be easily misidentified as those motivated by a fall. Conversely, if the two abovementioned 'sporting' ADLs are not taken into account, the highest 'distance' between the peaks and decays of falls and ADLs is accomplished through the measurements obtained with the sensor located on the wrist (e.g. the lowest first quartile of the SMV maximums provoked by the three types of falls is higher than the third quartile of the peaks caused by any of the 'moderate' – not sporting- ADLs). A quite similar behavior is achieved if the measurements with the sensor placed on the waist are considered. No further improvements seem to be obtained in case of employing the signals measured on the chest or on the trouser pocket. Thus, as a first approximation to the problem of fall detection, the combined use of two sensors placed on the wrist and waist could be proposed to characterize the mobility of the human body. The application of fall detection algorithms to the signals captured at both points simultaneously could avoid the false positives that can be produced by many arbitrary movements of the arms and hands (not considered among the ADLs simulated in the experiments).

Anyhow, future research should contemplate more sophisticated detection methods (such as those based on machine learning techniques) to assess the importance of the location of the sensor in FDS.

4. Conclusions

This paper has presented UMAFall, a dataset of movement traces, acquired during the execution of a wide set of ADLs (Activities of Daily Life) and three types of falls by 17 experimental subjects. In contrast to other existing datasets, these traces include the periodical measurements of up to five sensing points located on different positions of the body. The traces include the acceleration, gyroscope and magnetometer data captured simultaneously by four Bluetooth-enabled sensor motes as well as the signals sampled by the accelerometer embedded in a smartphone, which act as the data sink of a wearable wireless sensor network.

The dataset, which is publicly available in Internet [29] [30] and which is planned to be progressively augmented with new samples in the near future, is intended for the evaluation of fall detection systems. The presence of multiple sensors in the architecture employed to obtain the data can facilitate a systematic offline research of the impact of the sensor position on the efficacy of fall detectors.

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