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An analytical comparison of datasets of Real-World and simulated falls intended for the evaluation of wearable fall alerting systems

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A R T I C L E I N F O

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A B S T R A C T

Automatic fall detection is one of the most promising applications of wearables in the field of mobile health. The characterization of the effectiveness of wearable fall detectors is hampered by the inherent difficulty of testing these devices with real-world falls. In fact, practically all the proposals in the literature assess the detection algorithms with 'scripted' falls that are simulated in a controlled laboratory environment by a group of volunteers (normally young and healthy participants). Aiming at appraising the adequacy of this method, this work systematically compares the statistical characteristics of the acceleration signals from two databases with real falls and those computed from the simulated falls provided by 18 well-known repositories commonly employed by the related works. The results show noteworthy differences between the dynamics of emulated and real-life falls, which undermines the testing procedures followed to date and forces to rethink the strategies for evaluating wearable fall detectors.

1. Introduction

World Health Organization (WHO) has estimated that around 684 k mortal falls occur each year in the world, while 37.3 million falls require medical attention [1]. Most severe falls are suffered by adults older than 65 years. Roughly-one third of people aged over 65 fall each year and 5 % of these accidents result in a fracture [2].

A prompt assistance of the fallers is a key factor to reduce the medical consequences of falls. 'Long lies' (i.e. higher than 60 min) are linked to different co-morbidities (ranging from dehydration to pneumonia or hypothermia) and they have been found to increase up to 50 % the probability of dying within six months after the accident [3 4]. In such context, it comes as no surprise that the design of cost-effective and automatic alerting Fall Detection Systems (FDSs) has gained much research attention in recent years, becoming one of technologies with more potential in the field of telecare applications and, especially, the remote monitoring of biosignals. The numbers of research articles and patents on automatic FDSs have rocketed since 2010 (see the bibliographic study in [5] for a numerical analysis of this growth). Besides, the global market of Fall detection Systems is expected to be valued at US$ 600.0 Mn before 2030, expanding at a compound annual growth rate (CAGR) of approximately 4 % between 2019 and 2029 [6].

FDSs can be contemplated as an instance of Human Activity Recognition (HAR) systems. FDSs are binary pattern recognition systems oriented to permanently supervise the human actions so that a spurious movement caused by a fall can be discriminated from ordinary routines or ADLs (Activities of Daily Living). As soon as an accident is suspected, the FDS must issue an alerting message (SMS, email, phone call, app notification, etc.) to a remote caregiver (medical or nursing staff, user's relatives, etc.).

FDSs have been traditionally classified into two general groups. On one side, the operation of Context-Aware Systems (CAS) is grounded on the measurements of a set of sensing nodes (pressure sensors, microphones, cameras, radars, ultrasonic or infrared sensors, etc.) located on a predefined area (typically at home) around the person to be monitored. CAS solutions normally involve higher installation and maintenance expenditures as well as a fine adjustment and adaption of the tracking equipment to the particularities of the user's environment. In addition, the action of contextual detectors is restricted to a very particular zone, which could be only acceptable for certain setups (e.g. a nursing home). In fact, according to certain studies [7], between 28 % and 38 % of falls of the elderly occur out of their homes.

Contrariwise, wearable FDSs can be used regardless of the user's location since they base their detection decisions on signals acquired by

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sensors (mostly inertial measurement units –IMUs-) that are directly transported or worn by the patient. As abovementioned, when compared to CASs, wearable FDSs benefit from a higher ease of installation, more cost-efficiency and a simpler design and configuration [8]. Although other sensors (mainly gyroscopes but also occasionally magnetometers or even heart rate or electromyography -EMG- sensors) have been integrated in some prototypes, accelerometer is, by far, the most used sensor in the research of wearable fall detectors [9]. By virtue of the massive adoption of cellular technologies, wearable fall detectors can be easily endowed with long-range wireless connection interfaces that enable them to operate ubiquitously, as long as that radio coverage of the transmission standard is guaranteed. Wearable architectures thus provide a greater freedom of movement than context-aware solutions, at least in metropolitan settings where a mobile connection is almost always available. Furthermore, wearable detectors can benefit from the constantly declining prices of microelectromechanical systems as well as from the widespread popularity of certain personal devices (e.g. smartwatches, sport-bands, etc.). As a matter of fact, the review report presented by Xu et al. in [9] shows that the number of FDSs using cameras has greatly decreased since 2014, while the use of accelerometers in the research of FDSs is clearly expanding. On the contrary, concerns related to ergonomics and, more specifically, the autonomy of the battery-powered components of the fall detector can hinder the real use of transportable FDSs.

A crucial and very debatable aspect in the development of any FDS (either contextual or wearable) is the testing or validation of the detection algorithm. Obviously, a systematic evaluation of an FDS with actual falls of the target public (mainly the elderly) is inherently problematic. As pointed out by Khan & Hoey in [10], an experimental testbed aimed at monitoring real-life falls from older adults normally implies a complex setup that requires elevated operational costs, long-term facilities, the collaboration of external institutions, strict ethics clearance and significant time investment, as well as extensive computing resources for data analysis and an arduous process of data logging, extraction and labeling. Furthermore, even among frequent fallers, falls are extremely rare events when compared with other typical routines or ADLs. Thus, recording the inertial signals provoked by an actual fall is a laborious and time demanding operation. It has been estimated [11] that collecting 100 falls requires a monitoring time of 100,000 days (or a year if a population of 300 persons is employed).

By reason of these difficulties to obtain the inertial measurements produced by real falls, the vast majority of works on fall detectors have been traditionally evaluated using 'synthetic' datasets, i.e. samples generated under laboratory conditions, in a controlled testbed in which a group of volunteers simulate o 'mimic' falls. Nonetheless, these emulated falls respond to a very limited series of artificial and well-structured actions, in which the experimental subject is instructed to fall abruptly on a surface (which is usually cushioned) by following very rigid mobility patterns. The study carried out in this article tries to assess the adequacy of this testing procedure, as long as the dynamics of real falls may substantially differ from those exhibited by these simulations.

The paper is structured as follows: after this introduction, the precedents and review of the related literature are commented in Section 2. Section 3 describes the utilized datasets and the features considered for the characterization of the movements. Section 4 shows the obtained results and discusses them with respect to some previous findings of other works. Finally, the main conclusions are recapitulated in Section 5.

2. Related works

Currently, the wearable market offers a diversity of commercial off-the-shelf devices, explicitly conceived as fall detectors (see the reviews in [12,13,14] or [5]). These products, which typically adopt the form of a wristband or a pendant and normally also integrate a 'panic' button, are oriented to home monitoring scenarios, as their networking architecture is supported by a short-range base station located in the vicinity of the user. To avoid this limitation (and the additional costs of the landline connection required by the base-station), some recent high-end smartwatches, such as Samsung Galaxy Watch3 [15] or Apple Watch (since Series 4) [16], natively incorporate applications to detect falls. However, in all cases, the manufacturers do not give any specific detail about the procedure with which the application was validated or about the actual effectiveness of these commercial solutions to cope with real falls (and still less with falls of older people).

As it refers to the scientific literature on FDSs, almost all researchers are obliged to follow a 'laboratory' approach for the collection methodology of activity samples for the test phase. Thus, the evaluation datasets are generated by a group of participants that perform specific structured movements (ADLs and falls) in laboratory premises [17]. During these 'scripted' and preset experiments, the signals collected by the sensors (in the form of time series) are saved in a dataset of traces (manually identified as ADLs or falls), which are used to evaluate the performance of the movement classifiers in an 'offline' way.

Besides, although fall detectors are mainly conceived and intended for seniors, the involvement of older people (who are more vulnerable to falls) in any of the stages of the design, deployment or assessment of fall detection systems is extremely rare (see the scoping review by Thilo et al. in [18]). Young and healthy adults constitute the study population in most works on wearable FDSs, while older people are basically only considered to evaluate systems intended for fall risk screening (refer to the paper by Bet et al. in [19] for a more detailed study on this topic).

Already in 2014 a review paper on FDS authored by Chaudhuri et al. [20] drew attention to the fact that only 7 % of the projects proposing wearable fall detectors (4 out of 57) were tested in a real-world setting. The review of 2013 by Schwickert et al. [21], published a year earlier, provided a similar viewpoint: 90 of the 96 analyzed studies on FDSs were exclusively based on simulated fall data. Since then, the approach to evaluate FDSs has not changed significantly. In fact, recent states-of-the-art still bring to light and criticize the lack of real world testing of FDSs in actual application scenarios with older people [22 23 24]. Just a small group of works on wearable FDSs have validated their proposals in real long-term monitoring scenarios. Table 1 reviews those existing works, portraying the characteristics of the experimental subjects and the achieved long run results of the detector: percentage of detected falls, sensitivity and number of false alarms (see the scoping review by Bradley et al. in [25] for a deeper comparative analysis of some of these papers).

A group of these works correspond to pilot studies in nursing homes or care facilities, while in other articles the users are directly tracked in a home environment. In all the studies recapitulated in the table, the participants wore a single mote (mostly on the waist) except in the work by Aziz, where a sub-group of the volunteers transported four accelerometers (on both ankles, chest and waist). In almost all cases, the research is oriented to evaluate 'in-the-wild' the prototype developed by the authors. By contrast, the work by Bloch et al. [26] presented a study describing the results of a commercial accelerometer-based domotized detector applied to ten older persons with risks of falling in geriatric facilities.

In all the works in the table the detection algorithm is focused on the accelerometer signals, although in some papers they combine this information with the measurements of a gyroscope [27 28], orientation sensor [29] or magnetometer. The algorithms are normally implemented on a specific tracking wearable, although in the study by Harari et al. in [27] the participants (selected from a group of frequent fallers) were monitored while transporting a FDS implemented as an app on a smartphone (placed in a waist pouch).

Table 1 excludes those long-term monitoring experiences involving non wearable FDSs purely based on ambient sensors (radars, presence sensors, etc.) or video-cameras, such as those presented by Debard [39 40], Liu [41], Rezaee [42], Skubic [43] or Stone [44]. However, in some of the surveys mentioned by the table, the wearable solution is also

Table 1
Articles that evaluated wearable fall detectors through online long term montoring of subjects in a real scenario.

Reference	Number of Monitored Subjects	Scenario	Age (years)	Sensor Position	Total monitoring time (equivalent days)	Type of FDS	Number of detected falls/ total falls	Sensitivity	Number of false alarms
Aziz et al. [30][1]	9 10	Nursing home	76 to 94 56 to 75	Chest, waist ankles Waist	8.9 7.16	Machine learning model (SVM)	1/1 7/9	100.0 % 77.7 %	10 26
Barralon et al. [31]	20	Domestic	55 to 82	Waist	≈800 (approx.)	Threshold-based	n.i.[2]	93.4 %	53
Bloch et al. [26]	10	Nursing home	83.4 ± 7.5	Chest (thorax)	≈1400 (approx.)	Proprietary: Commercial device (Vigi'Fall)	5/8	62.5 %	25
Chaudhuri et al. [28]	16	Nursing home	n.i.[2]	n.i.[2]	1452.6	Proprietary: Commercial device	1/4	25.0 %	83
Feldwieser [32]	28	Domestic & outdoors	66 to 89	Waist (frontal pelvis region)	1225.7	n.i.[2]	10/15	66.6 %	4592
Gietzelt et al. [29]	3	Domestic	81 to 92	Waist (belt)	108	Threshold-based	2/9	22.2 %	[1.3–2.4] per user/day
Harari et al. [27]	23	Domestic	22 to 70	Waist	≈2070 (approx.)	Threshold-based + Machine learning model	27/37	73.0 %	45
Huq et al. [33]	29	Domestic	Up to 94	Huq	≈5220 (approx.)	Threshold-based	n.i./14	n.i.	456
Kangas et al. [34]	16	Domestic	88.4 ± 5.2	Waist	645.8	Threshold-based	12/15	80.0 %	748
Lipsitz et al. [35]	62	Nursing home	86.2 ± 8.1	Pendant around neck.	9300	Proprietary: Commercial Philips device	17/89	19.1 %	111
Mosquera-López et al. [36]	25	Domestic	33 to 76	Waist	1400	Threshold-based + Machine learning model	50/54	92.6 %	0.65 per day
Saleh et al. [37][2]	16	Nursing home	>80	Wrist /(9 subjects) or neck (7 subjects)	400	Threshold-based Machine learning	2/2	100.0 %	[3.5–11] per day [0.04–0.32] per day
Scheurer et al. [38]	20	Domestic	86.2 ± 6.7	Waist	125	Threshold-based	25/31	80.6 %	61

[1] The study analyzes the data from two experiments with different volunteers and monitoring conditions.
[2] n.i.: not indicated in the article.

complemented by a contextual or context-aware device (e.g. peripheral infrared detection system in the study by Bloch et al., a vision-sensor in [29] and a Kinect sensor in [32]).

In one of these works the use of emulated falls is not completely discarded. As a result of the scarce numbers of collected falls (only 2), the authors in [37] use a 'synthetic' dataset (FallAllD) to complement the evaluation of the proposed detector (which is tested in an offline way against the measurements collected during the long term monitoring).

In other cases, the algorithm is refined and re-reconfigured as the ongoing monitoring of the participants progresses and some errors are detected. Specifically, in the analysis provided by Scheurer [38], the study was divided into two phases. The results of the first phase were used to revise and fine-tune the parameters of the employed threshold-based algorithm so it could adapt to the particularities of the target population.

These works reveal that a not negligible percentage of false alarms are due to accidental drops or misuse of the detecting devices (in particular when the participants put them down). For example, Chaudhuiri et al. highlight in [28] that the sensitivity of the commercial detector employed in their analysis plummeted from 94 % (achieved by the vendor with 59 volunteers mimicking falls in a laboratory setting) to 25 % (1 out of 4 real falls) when it was tested in long term experiments in a real scenario.

The table does not include those studies that analyzed the behavior of FDSs when tested in an offline manner against the data collected during long term monitoring. In this vein, the study by Godfrey et al. in [45] presents the results of a HAR system, trained with the measurements from healthy subjects, when it was evaluated with the seven day accelerometer data gathered from a participant with low scores for balance self-efficacy. During the week under observation the subject suffered a fall, which was correctly identified (in an offline manner) by the proposed detector. Similarly, in [46], Hu et al. recruited five community-dwelling older adults who were asked to wear on the chest an inertial measurement unit (a SHIMMER mote) during two weeks. The participants, who maintained a journal or log of their activities, reported 20 falls (a very high value if we consider the size of the population and the observation period). In the obtained traces, the falls were manually identified and labelled and then used to assess a threshold-based detector. As in the work by Godfrey, the inertial data gathered during the falls were not made publicly available.

An offline evaluation of a FDS is also considered by Soaz et al. in [47]. Authors employ a subset of a database with more than 100,000 h of real-life accelerometry recordings. Though, as just one real fall is included in the original data, the dataset is completed with falls and fall-like activities simulated by young volunteers.

Similarly, Table 1 does not incorporate either those works that have utilized the real falls harvested in the FARSEEING project. For years this well-known dataset (which is described in more detail in the next section) has been practically the only repository containing real falls far used to systematically parametrize and benchmark FDSs. See, for example, the evaluation of the architectures proposed by Bagalá [11], Bourke [48], Chen [49], Palmerini in [50] or [51], Yu [52] or Alizadeh [53].

As it refers to the other repository used in our article (FFFStudy -Free from Fall Study- dataset, which is described in section 3), Clara Mosquera-Lopez et al. [36] developed three variants of a FDS which were tested with this dataset of real falls. Owing to the scarcity of falls, the proposals (which combined a thresholding approach and several machine learning techniques) were refined with the data of a well-known dataset of emulated falls (SisFall, also used in this work). The best performing method yield 92 % sensitivity and a rate of 0.65 false alarms per day.

In other works with a similar goal, the long-run test of the detectors concluded without any fall of the subjects under observation. Thus, the sensitivity of the movement classifier could not be calculated. For example, the fall detection method proposed by Angela Sucerquia et al. in [54] and parameterized according to SisFall dataset (also described in section 2), was assessed during several days on three older adults. During this period, all the participants developed their daily routines (including activities as cooking, washing clothes, reading, traveling by bus, climbing on stairs). No falls occurred but the system produced 16 false alarms. This is also the case of two studies authored by Bourke et al. in [55] and [56]. In the first one, five elderly subjects were tracked during 833 h while wearing a custom designed vest that integrated a garment with a fall detector. No falls were recorded but the system produced 42 fall-alerts. In the second article, 52.4 h of continuous normal activities were collected with a waist-worn accelerometer transported by ten healthy older adults. The captured dataset was inputted to a threshold-based FDS under different parameter configurations. The detection process resulted in three false positives. A smartwatch-based FDS was used by Van et al. [57] in a trial study with three senior volunteers for a period of about one month. No falls occurred but 83 false positives were registered (1.153 per person and day).

In this respect, in almost all the related literature, the capacity of FDSs to avoid false alarms has been traditionally evaluated by computing the specificity (or its complementary, the false positive rate), a typical quality metric in binary decision systems which, in the case of fall detectors, describes the percentage of actual ADLs (or -at least- non-falls events) which are correctly identified. When a 'synthetic' dataset is used for the evaluation, specificity can be straightforwardly estimated as there is a finite number of non-falls activities that the volunteers were asked to execute, following a predefined schedule that imposes the types of ADLs to be performed. However, this metric can be very misleading since it entirely relies on the nature of 'non-falls' (a slippery and controversial concept) included in the test repository. Furthermore, it is not clear how the specificity can be used as a guideline to quantify the performance of the system in a real scenario of permanent user monitoring. Due to the high numbers of ADLs or 'non-falls' that are daily performed, even an apparently high specificity may entail a high rate of false alarms. For example, as it is pointed out by Saleh [37], if the FDS has to produce one detection decision per second (86,400 decisions/day), a specificity of 99.99 % implies the generation of eight false positives per day. In this regard, the False Positive Rate over Time (FPRT) or frequency of false positive (calculated per day or per hour) [25] should be preferred to characterize the effectiveness of the detector to circumvent incorrect alerting messages. Nonetheless, this metric cannot be properly estimated in laboratory conditions.

Precision is another interesting alternative to specificity aimed at characterizing the reliability of the detector when an alerting message is generated. In the case of an FDS, precision defines the ratio between the number of correctly generated alarms and the total number of emitted alarms. As the review presented in Table 1 evince, the precision achieved by the classifiers when applied in long-term real conditions and realistic settings is always below 50 % (in some studies, below 1 %). For practical purposes, these data suggest that when an alarm occurs there is a very high probability that it is triggered by a misclassification of a non-fall or conventional movement. This undoubtedly undermines the confidence of the target public (whether they are healthcare institutions or individuals who require being monitored from their homes) in this type of assistive technologies. Even in nursing homes, false alarms are undesirable time-consuming events that provoke the disturbance of both the caregivers and the comfort and privacy of the patients.

In any case, the analysis of this literature about real-life pilots reflects the stark contrast between the good performance traditionally achieved when the detectors are evaluated with datasets of simulated falls (almost always with sensitivities above 90–95 % [5]) and the extreme under-performance of the proposals in scenarios of long-term monitoring of end users. Consequently, it is legitimate to ask whether the use of programmed falls emulated by volunteers has any practical value for the research on FDS.

A fall has been formally defined as 'an unexpected event in which the participants come to rest on the ground, floor, or lower level' [58], or as 'an involuntary change from standing, walking, bending, reaching, etc. to no longer being supported by both feet, accompanied by (partial or full) contact with the ground or floor' [59]. According to these definitions, falls are intrinsically unintentional acts, which would question any attempt to substitute them by voluntary actions.

The work by Kangas [60] (also discussed in [61]) was perhaps the first study that compared the dynamics of real falls and simulated falls specifically created to evaluate FDSs. The actual falls were gathered by attaching a wireless prototype sensor to the waist of 16 older adults (recruited in Sweden and Finland and with average age of 88.4 $\pm$ 5.2 years) during 6 or 2 months (depending on the experimental subjects). According to the analysis of the authors (which was mostly qualitative), some characteristics in the acceleration patterns of the real-life falls resemble those of the movements emulated in the laboratory. For example, both accidental and 'self-inflicted' falls may show a typical sequence of 'stages' including a pre-impact and impact phase. These authors also detected the existence of evident divergences. For example, the high pre-impact velocity towards the ground of mimicked falls is not always present in real-life falls. However, it must be noted that the study was based on only five real falls. In addition, in order to reduce consumption and extend the battery lifetime of the sensors, the sampling frequency was kept to a very low value (6.5 Hz) until the free-fall phase was suspected (by setting an inferior threshold of 0.75 g to the acceleration components). This value of the sampling rate (below 15–20 Hz) may result insufficient to properly characterize the human mobility during a fall [62 63].

When we observe in detail the descriptive videos that complement some public datasets, it is verified that, for the simulation of falls, the participants usually start from a stationary position and that, after the collapse, they tend to remain completely motionless on the ground. Similarly, when falling, volunteers avoid certain compensatory movements that are performed in real scenarios and that are oriented to cushion the impact, resulting in higher acceleration peaks when hitting the ground. This unrealistic behavior of the 'false' fallers discredits to some extent the validity of the simulations.

In most existing datasets the types of emulated falls basically differ in very few aspects, namely the initial position of the faller (standing, sitting, lying), the direction of the movement (forwards, lateral, backwards), and at best, the cause of the falls (tripping, slipping, fainting), which is almost always entirely simulated too. The fact is that the importance of the scenario and etiology of falls is normally underestimated in many studies on FDSs. For example, the falls experienced by residents in caring centers may notably differ from independent home-dwellers living by their own [64]. Most falls occur in a forward direction [65 66 67] when the subject is transferring or hurrying for some reason [66]. Besides, falls of older adults are mainly caused by trips and slips (54 %) as well as loss of balance (23 %) [68]. Moreover, due to the variety of situations that cause falls and the strong divergences in the physical conditions of the fallers, the dynamics of actual falls may range from sudden collapses or violent impacts to more gradual descents or controlled 'slumps' [35]. In some cases, before hitting the floor, the faller may impact against another object (a wall, a bed, a desk, etc.).

In this context, some researchers have been highly critical and skeptical on the evaluation of FDSs reliant on simulated falls. Emma Stack has widely and harshly criticized the use of 'fake' falls in [69], arguing that the focus should be on the study of real fallers and on the circumstances that cause falls. Stack emphasizes that falls are, by nature, involuntary acts, and, consequently, that falls cannot be -by definition- 'performed'. The author even questions the very ethics behind the studies on FDSs. In her opinion, they should avoid the term 'fall' and replace it by the more accurate 'intentional fall events'. Even in that case, laboratory-generated and real 'intentional' falls diverge, as the real ones (e.g. those experienced by people trying to commit suicide) are executed from a greater height. In the same work, Stack states that one of the key problems in the research field of automatic FDSs is that there are very few studies that have compared the data from actual and simulated falls. To fill this gap, we offer in this work a thorough and systematic comparison between a broad range of statistical characteristics computed from the acceleration signals captured during both actual and emulated falls. For this purpose, we utilize a wide set of repositories (totaling 18 datasets) of mimicked falls that have been commonly employed in the literature on FDSs, as well as two existing databases containing actual falls.

3. Materials and methods

3.1. Description of the employed datasets

For our analysis, we select two repositories resulting from long-term monitoring campaigns in which the participants were tracked during their daily routines while transporting an inertial sensor. To the best of our knowledge, these are the only existing datasets with actual falls that are publicly available. In order to compare the dynamics of these real accidents with that of the emulated falls, we review and choose a group of repositories containing 'synthetic' falls, deliberately designed as tools to evaluate wearable FDSs. The following paragraphs summarize the basic metadata of the databases used for the comparison as well as the procedure with which they were generated.

3.1.1. FARSEEING dataset

To date, the FARSEEING project [70], funded by the European Union, has been the most noteworthy initiative to gather a long scale repository with inertial measurements of real-world falls. Between January 2012 and December 2015, the six institutions contributing to the project monitored with sensors from different vendors the physical activity of over 2,000 participants, including community-dwelling older people and different groups of patients at high risk of falling.

During the project, more than 300 verified real-world fall events from 94 fallers with a mean age of 76.1 years were recorded. The whole dataset is not publicly available in Internet but at least the files containing the measurements of 22 falls can be accessed on request to the authors. These files are accompanied by a document that describes in detail the characteristics of the fallers and the circumstances of the falls.

These 22 falls correspond to 15 users (8 females and 7 males), aged between 56 and 86. The gait impairment was clinically classified as mild, moderate, severe and complete for 3, 8, 2 and 2 subjects, respectively. Besides, 7 out of the 15 subjects had some type of cognitive disability. Similarly, vision impairments were also documented for 7 subjects.

Depending on the participant, two different models of sensing IMU (Dynaport Hybrid or Pal Technologies ActivPAL3) and sensor placements were considered, so the measurements were alternatively obtained at 20 Hz or 100 Hz on the back waist (L5 or fifth lumbar spine vertebrae) or on the thigh. All the published traces have a duration of 1200 s and include the acceleration signals. Besides, those samples captured with the Dynaport Hybrid sensor also incorporated the information of the gyroscope. The exact moment in which each fall occurred was manually annotated and indicated in the documentation that accompanies the released dataset.

In all the samples (except in one, which is not documented), the subjects fell against the floor. The reported pre-fall activity for the 22 falls was walking (eight falls), bending to pick up and object (three falls), standing (seven falls) and transferring from a sitting to a standing position or vice versa (four falls). Just in one of the samples the faller was able to get up without help after the fall. Five out of the 22 falls resulted in injuries (scrapes, abrasions, bruises) of varying severity in different parts of the body (head and buttocks in one case, arm in two falls, back in one case and shoulder and thigh in another faller). Six falls required some type of medical intervention.

As it refers to the place of the accidents, 12 falls were recorded in a rehabilitation clinic (one in a corridor, six in the patient's room, four in the bathroom and one in the dining hall), one in a day care center and eight in the patients' homes (one in the kitchen, one in the entrance, three in the corridor, two in the living or dining room and one in the cellar). The exact location of one of the falls is unknown.

The FARSEEING repository is well known in the field of fall detectors and have been used by different studies. In a more recent work by Palmerini et al. in [51], an extended version of FARSEEING with 143 falls is presented. However, this extended version of the repository is not publicly available yet. Also recently, another dataset, including 403 annotated falls from 537 test subjects has been collected for the Fall-Sensing project [71]. Regrettably. the data have not been still undisclosed.

3.1.2. FFFStudy dataset

The Free From Falls (FFF) Study [36], developed by the Veterans Affairs Portland Health Care System and the Oregon Health & Science University, enrolled 34 people (aged between 33 and 76) with a confirmed diagnosis of multiple sclerosis but with the ability to walk at least 100 m with or without assistance and the ability to provide an informed consent and to adhere to the protocol of the monitoring campaign. The participants, who were monitored during eight weeks, were requested to carry on a belt (front waist) a MotioSens MotioWear sensor tag [72]. This wireless wearable sensing mote is capable of measuring and storing the IMU data as well as the user indoor or outdoor localization.

After discarding five subjects for personal or technical problems and another four used to fine-tune and parametrize the model, a dataset with the acceleration measurements (sampled at 50 Hz) and localization information (not employed in this study) captured from 25 subjects during 8 weeks was generated. In the description of the dataset (publicly accessible in Internet), authors indicate that 54 falls –lasting less than 5 s- were captured (all in indoor areas). However, from the log provided in the related documentation (which indicates the instant - within the collected traces- in which the falls occur), just 49 were retrieved. Apart from these data about the timing, the authors do not offer any further detail or contextual information of the falls (e.g. cause, medical status of the faller, activity previously performed before the accident, etc.).

3.1.3. Datasets with emulated falls

Currently, over 25 datasets with simulated falls and ADLs have been disclosed as public benchmarking resources for the research on wearable fall detectors (see [73] for an extensive review on this topic). Unfortunately, the generation of these traces did not follow a shared guideline. In fact, the only common characteristic is that they incorporate the measurements of an accelerometer transported by the volunteers during the experiments. In this respect, there is a strong heterogeneity not only as it refers to the typology or number of simulated falls, but also on some operational aspects such as the sampling frequency (which ranges from 18 to 238 Hz) or the body location where the accelerometer was placed. As the position selected for the sensor in the two datasets with real falls was the waist, we selected those repositories in which there were traces gathered on that location or -at least- on the hip or thigh (which are in the vicinity of the waist). Thus, we discarded those datasets for which the accelerometer was placed on the wrist (DU-MD [74], HFID [75], SmartFall and Smartwatch datasets [76]), ankle (AnkFall [77]) or chest (CGU-BES [78]). In this regard, the performance and configuration of a wearable FDS strongly rely on the position of the sensor. Numerous studies [79 80 81 8283] agree that the optimal location for an on-body inertial sensor intended for fall detection is the waist, trunk or chest (and to a lesser extent, thigh [84]) since they are closer to the center of mass of the human body (typically about 10 cm lower than the navel in a standing posture). Additionally, we also rejected SMotion dataset [85] (although it was collected with a sensor on the waist) since it only contains five mimicked falls.

Following this screening based on the sensor placement, we finally chose 18 datasets for our research. In one of them, ADLs correspond to real life inertial measurements in free living conditions. However, all the falls in these repositories were scripted and simulated in laboratory conditions. In the rare cases where the volunteer group included older people, they were usually exempted from simulating falls for safety reasons. The basic characteristics of these repositories are synopsized in Table 2. The table also indicates the number of types and samples of ADLs provided by these databases although the study will be mainly focused on the dynamics of falls. Similarly, the table also indicates all the positions of the sensors used in the different testbeds. When a dataset contains the inertial measurements collected on different locations, our comparison will be limited to those captured on the waist, or, failing this, the hip or thigh (which is indicated in parentheses next to the repository name.

3.2. Selection of statistical features

In this subsection, we describe the statistics considered to compare the dynamics of real and emulated falls of the datasets under study. All the employed statistics are derived from the accelerometer measurements since (as shown in Table 1), acceleration is the only variable present in all the repositories and the only one provided by the datasets with real falls. As already mentioned, acceleration is by far the signal most massively used by the related studied to feed the classifier in wearable FDSs. The advantages of complementing the acceleration signals with other type of inertial data (in particular, the angular velocity collected by the gyroscope) to improve the detection ratio of is still a topic under debate [104].

Given the great heterogeneity of the measurement intervals of the movements offered by the databases, in order to define a common characterization framework, the statistical analysis of the acceleration will focus on an 'observation window' (or time interval) of fixed duration. When the subject's body collides with the floor, harsh and abrupt peaks of acceleration typically occur [105]. Hence, for each trace (or fall) in the datasets, the observation window will be centered around the instant where the maximum acceleration magnitude is detected. For the i-th measurement collected during a certain fall, this acceleration Signal Magnitude Vector (SMV_i) of the acceleration is defined as:

$$SMV_i = \sqrt{A_{x_i}^2 + A_{y_i}^2 + A_{z_i}^2} \tag{1}$$

where A_{x_i}, A_{y_i} and A_{z_i} describe the x, y, and z triaxial components gathered by the accelerometer. From this series, the index (i_{max}) of the sample in which the maximum SMV (SMV_{max}) takes place is found as:

$$SMV_{max} = SMV_{i_{max}} = max\{SMV_j : j \in [1, N]\} \tag{2}$$

where N indicates the total number of inertial measurements in the trace.

Banos et al. have shown in [106] that an analysis interval of 1–2 s provides the best trade-off between recognition speed and effectiveness to identify most human activities. In this context, it has been stated that 5–6 s is enough to recognize a fall pattern [107]. The unexpected and jerky movements caused by most falls usually last between one and three seconds [108]. In fact, the 'critical phases' of a 'domestic' fall, including the 'free-fall' period and the vertical shock against the ground, do not take more than 0.5–0.85 s [109 110 111]. In the related literature on fall detection, there are many examples of algorithms that base their detection strategies on analyzing the behavior of the inertial signals in particular temporal windows where a fall is suspected. To this effect, windows from 0.2 to 2 s have been considered although the most common values range between 0.5 and 1 s [76]. On that basis, we established an observation window (T) of 2 s around the maximum (1 s before and after the detected peak) for each trace to incorporate the most relevant components of the dynamics of the falls. In any event, very similar conclusions and results -not presented in this article for space reasons- were obtained when other sizes of the observation window (3 or 4 s) were contemplated. As already noted, in the case of the datasets with actual falls (captured by long term monitoring programs), authors inform about the exact instant in which the subject experienced the real falls. Therefore, we used this information to locate the corresponding observation window of 2 s.

All the measurements collected out of these observation intervals were ignored to calculate the statistics, which were computed just from the segments of the original series corresponding to the triaxial acceleration components and acceleration magnitude measured in this time interval, which can be defined as:

$$\left\{A_{x_j}, A_{y_j}, A_{z_j}, SMV_j : j \in \left[\left\lceil i_{max} - \frac{T}{2} f_s \right\rceil, \left\lceil i_{max} + \frac{T}{2} f_s \right\rceil\right]\right\} \tag{3}$$

where f_s defines the sampling rate used to capture the trace and the operator $\lceil x \rceil$ rounds the value of x to the lowest integer greater than x.

For comparison purposes, we characterize the falls in all datasets by calculating fifteen statistical features, commonly used by the literature in HAR and FDSs (for both threshold-based and machine-learning approaches). See, for example, the features employed by the detectors presented in [97 112113 80 114 115 116 90 117 118 119 120 54 121 122] or the comprehensive review presented by Vallabh in [123] or by Xi in [124].

The selected features are analytically defined as it follows:

1. The aforementioned peak or maximum ($\boldsymbol{SMV_{max}}$) of SMV_i, as a meaningful descriptor of the force of the impact against the ground.
2. The minimum value achieved by the acceleration magnitude ($\boldsymbol{SMV_{min}}$) before the peak, as a key element to describe the free-fall phase:

$$SMV_{min} = SMV_{i_{min}} = min\left\{SMV_j : j \in \left[\left\lceil i_{max} - \frac{T}{2} f_s \right\rceil, i_{max}\right]\right\} \tag{4}$$

where i_{min} is the index of the sample where $\boldsymbol{SMV_{min}}$ is found.

3. The mean Signal Magnitude Vector ($\boldsymbol{\mu_{SMV}}$), which informs about the average body motion intensity during the fall:

$$\mu_{SMV} = \frac{1}{N_W} \cdot \sum_{j=\left\lceil i_{max} - \frac{T}{2} f_s \right\rceil}^{\left\lceil i_{max} + \frac{T}{2} f_s \right\rceil} SMV_j \tag{5}$$

where N_W defines the number of acceleration samples contained in the observation window, computable as:

$$N_W = 2\left\lceil \frac{T}{2} f_s \right\rceil + 1 \tag{6}$$

4. The standard deviation ($\boldsymbol{\sigma_{SMV}}$) of SMV_i, which describes the variability of the acceleration during the observation window:

$$\sigma_{SMV} = \sqrt{\frac{1}{N_W - 1} \cdot \sum_{j=\left\lceil i_{max} - \frac{T}{2} f_s \right\rceil}^{\left\lceil i_{max} + \frac{T}{2} f_s \right\rceil} \left(SMV_j - \mu_{SMV}\right)^2} \tag{7}$$

Table 2
Characteristics of the employed datasets with emulated falls.

Dataset	Ref.	No. Subjects (Females/ Males)	Age range (years)	Number of types of ADLs/ Falls	Number of samples (ADLs/ Falls)	Duration of the samples (s)	Number of sensing points	Number &type of Sensors[1]	Positions of the sensing Points	Type of device[1]	Sampling rate (Hz)	Accel. range (g)
CMDFALL	[86]	50 (20/30)	21 to 40	12/08	1000 (600/400)	450 s[2]	2	1 (A)	Left wrist, left hip	IMU	50	±16
Cogent Labs	[87]	42 (6/36)	18 to 51	8/6	1968 (1520/448)	[0.53–55.73]	2	2 (A,G)	Chest, Thigh	IMU	100	±8
DLR	[88]	19 (8/11)	23 to 52	15/1	1017 (961/56)	[0.27–864.33]	1	3 (A, G, M)	Waist (belt)	IMU	100	±5
DOFDA	[89]	8 (2/6)	22 to 29	1/5	432 (120/312)	1.96–17.262	1	4 (A, G, O, M)	Waist	IMU	33	±16
Erciyes	[90]	17 (7/10)	19 to 27	16/20	3302(1476/ 1826)	[8.36–37.76]	6	3(A, G, M)	Chest, Head, Ankle, Thigh, Wrist, Waist	IMUs	25	±16
FallAllD	[91]	15 (7/8)	21 to 53	44/35	6605 (4883/ 1722)[3]	20	3	4 (A, G, M, B)	Waist, Wrist, Chest	IMU	238	±8
Gravity Project	[92]	2 (n.i.)[3]	26 to 32	7/12	117 (45/72)	[9.00–86.00]	2	1 (A)	Thigh Wrist	SP, SW	50 (SP), 157 (SW)	±16
Graz UT OL	[93]	5 (n.i.)	n.i.[3]	10/4	2460 (2240/220)	[0.18–961.23]	1	2 (A, O)	Waist (belt bag)	SP	5	±2
IMUFD	[94]	10 (n.i..)	n.i.[3]	8/7	600(390/210)	[15–20.01]	7	3(A, G, M)	Chest, Head, Left & right ankles, Left & right thighs, Waist	IMU	128	±16
KFall	[95]	32 (0/32)	24.9 ± 3.7	21/15	5075 (2729/ 2346)	[2.03–40.86]	1	A, G, O	Waist (Low back)	IMU	100	±16
MobiAct	[96]	57 (15/42)	20 to 47	9/4	2526 (1879/647)	[4.89–300.01]	1	3 (A, G, O)	Thigh (trouser pocket)	SP	87 (A), 100 (G,O)	±2
SisFall	[97]	38 (19/19)	19 to 75	19/15	4505 (2707/ 1798)	[9.99–179.99] s	1	3 (A, A, G)	Waist	IMU	200	±16
tFall	[98]	10 (3/7)	20 to 42	MRLM[4]/8	10,909 (9883/ 1026)	6 s (all samples)	1	1 (A)	Thigh (pocket), or Hand bag	SP	45 (±12)	±2
TST	[99]	11 (n.i.)	22 to 39	4/4	264 (132/132)	[3.84–18.34] s	2	1 (A)	Waist, Wrist	IMUs	100	±8
UMAFall	[100]	19 (8/11)	18 to 68	12/3	746 (538/208)	15 s (all samples)	5	3(A, G, M)	Ankle, Chest, Thigh, Waist, Wrist	SP & IMU	100 (SP), 20 (IMU)	±16
UniMiB SHAR	[101]	30 (24/6)	18 to 60	9/8	7013 (5314/ 1699)	1 s (all samples)	1	1 (A)	Thigh (left or right trouser pocket)	SP	50	±2
UP-Fall	[102]	17 (8/9)	18 to 24	6/5	559 (304/255)	[9.409–59.979]	5	2 (A, G)	Ankle, Neck, Thigh (pocket), Waist, Wrist	IMUs	Around 18 Hz	±8
UR Fall Detection	[103]	6 (0/6)	n.i.[3] (over 26)	5/4	70 (40/30)	[2.11–13.57]	1	1 (A)	Waist (near the pelvis)	IMU	256	±8

[1] A: Accelerometer, G: Gyroscope, O: Orientation Sensor, M: magnetometer, SP: Smartphone, IMU: (stand alone) Inertial Measurement Unit, SW: Smartwatch.
[2] For CMDFALL dataset, all the 20 programmed movements are executed in a continuous manner during 7.5 min.
[3] n.i.: not indicated in the article.
[4] MRLM: Monitoring of real life movements (subjects did not perform a set of predefined activities).

5. The skewness of SMV_i (γ_{SMV}), which characterizes the symmetry of the distribution of the values of the acceleration magnitude:

$$\gamma_{SMV} = \frac{1}{\sigma_{SMV}^3 \cdot N_W} \cdot \sum_{j=\left\lceil i_{max}-\frac{T}{2}f_s \right\rceil}^{\left\lceil i_{max}+\frac{T}{2}f_s \right\rceil} \left(SMV_j - \mu_{SMV}\right)^3 \tag{8}$$

6. The 'valley-to-peak' time ($t_{v\text{-}p}$), i.e. the duration of the interval elapsed between the acceleration minimum (SMV_{min}) and maximum (SMV_{max}), which is straightforwardly calculable as:

$$t_{v-p} = \frac{1}{f_s}(i_{max} - i_{min}) \tag{9}$$

7. The duration of the free fall period (t_{ff}), computed as the time between the last sample before the minimum and the first sample after the minimum in which the acceleration magnitude exceeded a certain decision threshold (Th_{ff}). In our analysis, this threshold was set up to a value of 0.9 g, slightly below the gravitational acceleration on Earth (1 g or 9.8 m/s^2), which is the magnitude measured by the accelerometer at rest.

   The time of free fall period t_{ff} is calculated as:

$$t_{ff} = \frac{1}{f_s}(i_{ff\_end} - i_{ff\_start}) \tag{10}$$

where i_{ff_end} and i_{ff_start} respectively denote the indices of the last and first samples in the interval, defined as:

$$i_{ff\_end} = min\{j : j \in [i_{min}, i_{max}] \wedge SMV_j > Th_{ff}\} \tag{11}$$

$$i_{ff\_start} = max\{j : j \in \left[i_{max} - \frac{T}{2}f_s, i_{min}\right] \wedge SMV_j > Th_{ff}\} \tag{12}$$

8. The mean absolute difference ($\mu_{SMV_{diff}}$) between two successive samples of the acceleration magnitude, which is estimated as:

$$\mu_{SMV_{diff}} = \frac{1}{N_W - 1} \cdot \sum_{j=\left\lceil i_{max}-\frac{T}{2}f_s \right\rceil}^{\left\lceil i_{max}+\frac{T}{2}f_s \right\rceil - 1} \left|SMV_{j+1} - SMV_j\right| \tag{13}$$

This parameter offers an insight into the brusque fluctuations of the acceleration during a fall [125]. As it is clearly influenced by the sampling rate used to generate the dataset (since it directly determines the time between consecutive samples), for comparison purposes all the sequences are resampled to a common frequency of 20 Hz before computing this feature.

9. Number of peaks or local maxima (n_{peaks}) detected during the observation window. This statistic may inform about the presence of diverse impacts during the fall. A sample is considered to contain a peak when two conditions are met: 1) the acceleration magnitude of the acceleration measurement is higher than that of its two neighboring samples, 2) the acceleration magnitude surpasses a predetermined threshold (Th_{peak}), which was fixed to 2 g. This value is coherent with those selected in threshold-based detection algorithms to discriminate a fall occurrence (e.g. 2 g in [60 126], 1.8 g in [36], or 2.25 g in [37]).
10. The Signal Magnitude Area (***SMA***) [97]. This statistic, which is commonly employed to characterize the physical activity in HAR systems, is computed from the three acceleration components during the whole observation window:

$$SMA = \frac{1}{N_W} \cdot \sum_{j=\left\lceil i_{max}-\frac{T}{2}f_s \right\rceil}^{\left\lceil i_{max}+\frac{T}{2}f_s \right\rceil} \left(\left|A_{x_j}\right| + \left|A_{y_j}\right| + \left|A_{z_j}\right|\right) \tag{14}$$

11. Energy (E). To describe the energetic and brusque movements caused by the falls, we also take into account the sum of the energy approximated for the three acceleration axes during the observation window [122]:

$$E = \frac{1}{f_s} \cdot \sum_{j=\left\lceil i_{max}-\frac{T}{2}f_s \right\rceil}^{\left\lceil i_{max}+\frac{T}{2}f_s \right\rceil} \left(\left|A_{x_j}\right|^2 + \left|A_{y_j}\right|^2 + \left|A_{z_j}\right|^2\right) \tag{15}$$

12. The mean rotation angle (μ_θ) allows detecting the intensity of the alterations of the body orientation caused by falls [125]. This parameter is computed as the mean of the series of angles between consecutive acceleration vectors:

$$\mu_\theta = \frac{1}{N_W - 1} \cdot \sum_{j=\left\lceil i_{max}-\frac{T}{2}f_s \right\rceil}^{\left\lceil i_{max}+\frac{T}{2}f_s \right\rceil - 1} \left(cos^{-1}\left[\frac{A_{x_j} \cdot A_{x_{j+1}} + A_{y_j} \cdot A_{y_{j+1}} + A_{z_j} \cdot A_{z_{j+1}}}{SMV_{j+1} \cdot SMV_j}\right]\right) \tag{16}$$

Again, as this parameter is strongly influenced by the sampling rate, before calculations, all the series in the datasets are resampled to a common frequency of 20 Hz.

13. Gravity has a substantial effect on the acceleration component that is perpendicular to the floor plane. If the subject initiates the fall from an upright posture, subsequent movements most probably result in a significant change of the acceleration components that are parallel to the ground plane. To characterize these changes relative to the initial position, we also compute the mean magnitude (μ_{Ap}) of the vector generated by these two acceleration components:

$$\mu_{Ap} = \frac{1}{N_W} \cdot \sum_{j=\left\lceil i_{max}-\frac{T}{2}f_s \right\rceil}^{\left\lceil i_{max}+\frac{T}{2}f_s \right\rceil} \sqrt{\left(A_{H1_j}\right)^2 + \left(A_{H2_j}\right)^2} \tag{17}$$

where the two variables (A_{H1_j}, A_{H2_j}) represent the two components orientated in the horizontal plane before the fall. For each dataset, these components (*x&y*, *x&z* or *y&z*) obviously depend on the particular orientation with which the inertial sensing unit was attached to the volunteers' waist (or hip or thigh).

14. To characterize the acceleration signal in the frequency domain, we estimate the not-null frequency at which the maximum power spectrum of the acceleration magnitude is found (f_{maxPS}). For that purpose, the spectrum is calculated from the periodogram by using the Matlab *pspectrum* script [127]. To avoid the constant offset at 0 Hz introduced by the gravity in the body acceleration, the sequences of SMV are previously filtered with a high pass filter with a passband frequency of 0.2 Hz and a stopband attenuation of 60 dB.

15. During a regular activity, human acceleration presents a certain degree of self-correlation that can be disrupted by the jerky movements generated by a fall. To identify this loss of motion continuity, we employ the mean of the autocorrelation coefficients ($\boldsymbol{\mu_R}$) of the magnitude of the acceleration, defined as:

$$\mu_R = \frac{1}{N_W - 1} \cdot \sum_{l=1}^{N_W - 1} R_l \tag{18}$$

where R_l indicates the l-th lag value in the normalized series of the autocorrelation coefficients of SMV:

$$R_l = \frac{1}{\sigma_{SMV}^2 \cdot N_W} \cdot \left(\sum_{i=\left\lceil i_{max} - \frac{T f_s}{2} \right\rceil}^{\left\lceil i_{max} + \frac{T f_s}{2} \right\rceil - l - 1} \left(SMV_j - \mu_{SMV}\right)\left(SMV_{j+l} - \mu_{SMV}\right) \right) \text{ for } l = 0, 1, \cdots N_W - 1 \tag{19}$$

As the correlation between two consecutive samples obviously also depend on the sampling rate, we also applied a resampling technique (to a common general value of 20 Hz) to all the series of the acceleration magnitude in the datasets before computing this feature.

4. Results and discussion

Table 3 (for features 1 to 8) and Table 4 (for features 9 to 15) show the mean and the 95 % confidence interval computed for the 15 statistics used to characterize the fall movements in the 20 datasets under study (2 with real falls and 18 with emulated falls). For each feature, the two last rows in the tables indicate the number of 'synthetic' datasets in which the corresponding characteristic presents a significantly different mean (i.e. confidence intervals do not overlap) with respect to that computed for the actual falls of FFFStudy (second last row) and FARSEEING (last row) repositories.

These two rows expose the remarkable discrepancy between the 'laboratory-generated' and the real-life fall datasets, especially when comparing to the FFFStudy traces. Furthermore, for some statistics, there are statistically significant divergences between the mean value computed for FFFStudy and that obtained for almost all the synthetic datasets.

A detailed analysis of the tables also leads to the following conclusions:

- The simulated falls present a higher degree of abruptness and 'violence', which is reflected in higher values of the maximum ($\boldsymbol{SMV_{max}}$) and the average ($\boldsymbol{\mu_{SMV}}$) of the acceleration magnitude as

Table 3
Stastistical features (1 to 8) of the datasets (mean ± 95 % confidence interval).

Dataset	SMV_{max} (g)	SMV_{min} (g)	μ_{SMV} (g)	σ_{SMV} (g)	γ_{SMV}	$t_{v\text{-}p}$ (s)	t_{ff} (s)	$\mu_{SMV_{diff}}$ (g)
FFFStudy	3.494 ± 0.427	0.487 ± 0.055	1.054 ± 0.012	1.054 ± 0.012	4.012 ± 0.529	0.249 ± 0.069	0.081 ± 0.020	0.216 ± 0.023
FARSEEING	4.561 ± 1.086	0.287 ± 0.072	1.116 ± 0.045	1.116 ± 0.045	2.735 ± 0.541	0.250 ± 0.079	0.142 ± 0.045	0.329 ± 0.052
CMDFALL (Hip)	4.389 ± 0.127	0.409 ± 0.018	1.143 ± 0.012	1.143 ± 0.012	3.299 ± 0.140	0.409 ± 0.024	0.295 ± 0.055	0.319 ± 0.009
CogentLabs (Thigh)	4.061 ± 0.159	0.310 ± 0.021	1.120 ± 0.007	1.120 ± 0.007	2.330 ± 0.116	0.254 ± 0.014	0.092 ± 0.008	0.304 ± 0.010
DLR	5.218 ± 0.484	0.362 ± 0.040	1.127 ± 0.025	1.127 ± 0.025	3.784 ± 0.474	0.386 ± 0.070	0.288 ± 0.138	0.370 ± 0.035
DOFDA	6.369 ± 0.276	0.317 ± 0.014	1.137 ± 0.011	1.137 ± 0.011	4.125 ± 0.153	0.347 ± 0.022	0.446 ± 0.057	0.414 ± 0.013
Erciyes	4.204 ± 0.233	0.243 ± 0.007	1.076 ± 0.007	1.076 ± 0.007	2.865 ± 0.038	0.208 ± 0.005	0.309 ± 0.008	0.298 ± 0.012
FallAllD	5.839 ± 0.188	0.290 ± 0.014	1.121 ± 0.006	1.121 ± 0.006	4.044 ± 0.154	0.420 ± 0.023	0.189 ± 0.037	0.348 ± 0.012
GravityPro (Thigh)	1.456 ± 0.068	0.046 ± 0.007	0.343 ± 0.019	0.343 ± 0.019	1.860 ± 0.200	0.704 ± 0.049	1.840 ± 0.101	0.157 ± 0.009
UTOL	0.392 ± 0.050	0.071 ± 0.009	0.186 ± 0.022	0.186 ± 0.022	0.824 ± 0.088	0.477 ± 0.030	1.397 ± 0.042	0.041 ± 0.005
IMUFD	6.349 ± 0.299	0.270 ± 0.019	1.315 ± 0.016	1.315 ± 0.016	2.738 ± 0.134	0.499 ± 0.035	0.351 ± 0.087	0.450 ± 0.015
KFall	4.685 ± 0.034	0.207 ± 0.005	1.083 ± 0.002	1.083 ± 0.002	3.146 ± 0.028	0.235 ± 0.007	0.286 ± 0.012	0.328 ± 0.003
MobiAct (Thigh)	2.651 ± 0.022	0.320 ± 0.011	1.076 ± 0.004	1.076 ± 0.004	1.553 ± 0.050	0.344 ± 0.017	0.169 ± 0.022	0.287 ± 0.005
SisFall	6.646 ± 0.129	0.261 ± 0.006	1.111 ± 0.004	1.111 ± 0.004	4.235 ± 0.063	0.254 ± 0.008	0.222 ± 0.011	0.360 ± 0.005
tFall (Thigh)	2.621 ± 0.022	0.241 ± 0.009	1.027 ± 0.005	1.027 ± 0.005	1.278 ± 0.040	0.266 ± 0.012	0.186 ± 0.013	0.294 ± 0.005
TST	6.008 ± 0.253	0.257 ± 0.021	1.095 ± 0.008	1.095 ± 0.008	4.381 ± 0.215	0.260 ± 0.032	0.170 ± 0.021	0.372 ± 0.013
UMAFall	4.641 ± 0.288	0.324 ± 0.021	1.103 ± 0.010	1.103 ± 0.010	3.264 ± 0.180	0.279 ± 0.022	0.250 ± 0.021	0.379 ± 0.017
UniMiB (Thigh)	2.790 ± 0.017	0.267 ± 0.007	1.013 ± 0.003	1.013 ± 0.003	1.726 ± 0.033	0.223 ± 0.007	0.312 ± 0.011	0.272 ± 0.003
UPFall	3.397 ± 0.113	0.309 ± 0.016	1.080 ± 0.008	1.080 ± 0.008	2.136 ± 0.103	0.296 ± 0.016	0.329 ± 0.032	0.313 ± 0.010
UR	7.177 ± 0.763	0.317 ± 0.058	1.248 ± 0.039	1.248 ± 0.039	4.678 ± 0.535	0.314 ± 0.066	0.115 ± 0.041	0.405 ± 0.040
Datasets with a significantly different mean with respect to FFFStudy	16	18	18	18	12	7	16	18
Datasets with a significantly different mean with respect to FARSEEING	11	4	6	6	11	5	11	5

Table 4
Stastistical features (9 to 15) of the datasets (Mean ± 95 % confidence interval).

Dataset	n_{peaks}	SMA (g)	Energy	μ_θ(deg)	μ_{AP}(g)	f_{maxPS} (Hz)	μ_R
FFFStudy	1.204 ± 0.275	1.526 ± 0.034	2.510 ± 0.132	13.413 ± 1.472	0.640 ± 0.051	4.288 ± 1.100	−0.153 ± 0.041
FARSEEING	3.364 ± 0.849	1.639 ± 0.072	3.489 ± 0.571	25.094 ± 3.473	0.774 ± 0.081	2.651 ± 0.936	−0.141 ± 0.052
CMDFALL (Hip)	2.419 ± 0.152	1.675 ± 0.018	3.037 ± 0.080	17.862 ± 0.566	0.780 ± 0.017	2.943 ± 0.260	−0.136 ± 0.011
CogentLabs (Thigh)	3.185 ± 0.196	1.592 ± 0.014	3.116 ± 0.089	18.827 ± 0.529	0.694 ± 0.017	1.905 ± 0.216	−0.155 ± 0.012
DLR	2.143 ± 0.407	1.669 ± 0.039	2.661 ± 0.131	16.947 ± 1.343	0.782 ± 0.043	3.375 ± 0.629	−0.150 ± 0.028
DOFDA	2.311 ± 0.116	1.644 ± 0.018	4.330 ± 0.186	20.298 ± 0.454	0.767 ± 0.016	2.725 ± 0.214	−0.196 ± 0.012
Erciyes	1.217 ± 0.024	1.445 ± 0.012	4.204 ± 1.396	11.985 ± 0.169	0.676 ± 0.008	0.086 ± 0.020	−0.180 ± 0.005
FallAllD	4.335 ± 0.275	1.615 ± 0.012	3.375 ± 0.077	19.591 ± 0.585	0.757 ± 0.014	2.957 ± 0.211	−0.183 ± 0.010
GravityPro (Thigh)	0.083 ± 0.086	0.594 ± 0.033	0.445 ± 0.039	0.000 ± 0.000	0.280 ± 0.015	1.389 ± 0.250	−0.028 ± 0.016
UTOL	0.024 ± 0.016	0.275 ± 0.032	0.174 ± 0.040	16.823 ± 0.589	0.124 ± 0.015	0.781 ± 0.124	−0.088 ± 0.013
IMUFD	6.681 ± 0.324	1.937 ± 0.027	5.269 ± 0.223	24.347 ± 0.612	0.928 ± 0.020	1.449 ± 0.132	−0.096 ± 0.008
KFall	2.819 ± 0.054	1.464 ± 0.005	3.267 ± 0.019	16.329 ± 0.234	0.791 ± 0.004	2.332 ± 0.034	−0.080 ± 0.003
MobiAct (Thigh)	2.456 ± 0.103	1.614 ± 0.008	2.608 ± 0.024	19.913 ± 0.373	0.771 ± 0.008	2.990 ± 0.145	−0.157 ± 0.008
SisFall	3.766 ± 0.134	1.587 ± 0.007	3.766 ± 0.057	18.588 ± 0.313	0.788 ± 0.006	2.374 ± 0.048	−0.122 ± 0.004
tFall (Thigh)	1.974 ± 0.064	1.485 ± 0.009	2.488 ± 0.024	20.416 ± 0.361	0.705 ± 0.008	2.527 ± 0.089	−0.167 ± 0.007
TST	2.341 ± 0.246	1.573 ± 0.017	3.506 ± 0.108	15.992 ± 0.828	0.712 ± 0.015	3.209 ± 0.197	−0.176 ± 0.015
UMAFall	1.270 ± 0.076	1.530 ± 0.019	3.681 ± 0.196	18.653 ± 0.662	0.757 ± 0.014	1.870 ± 0.136	−0.180 ± 0.013
UniMiB (Thigh)	2.344 ± 0.060	1.464 ± 0.006	2.452 ± 0.015	18.268 ± 0.275	0.697 ± 0.005	1.984 ± 0.047	−0.154 ± 0.006
UPFall	1.259 ± 0.063	1.563 ± 0.018	3.249 ± 0.096	13.774 ± 0.492	0.741 ± 0.019	1.758 ± 0.101	−0.137 ± 0.015
UR	3.233 ± 0.552	1.859 ± 0.059	4.558 ± 0.510	20.206 ± 1.726	0.914 ± 0.042	2.628 ± 0.625	−0.095 ± 0.044
Datasets with a significantly different mean with respect to FFFStudy	15	14	14	16	16	14	4
Datasets with a significantly different mean with respect to FARSEEING	9	9	8	16	5	4	2

well as in the Signal Magnitude Area (SMA) or in the variations between successive samples ($\mu_{SMV_{diff}}$) derived from the *SMV*.

- The number of acceleration peaks (n_{peaks}), the variability of the acceleration module around the mean (described by the deviation σ_{SMV}) and the required energy (E) is also greater in the emulated falls.
- The phases of free fall (t_{ff}) and the interval between the valley and the peak of the acceleration ($t_{v\text{-}p}$) are clearly longer in the simulated falls (longer values of $t_{v\text{-}p}$ and t_{ff}).
- The mean body rotation angle (μ_θ) and the importance of the acceleration components horizontally oriented at the beginning of the movement (μ_{Ap}) are also higher in the series corresponding to the simulations.
- Simulated falls do not seem to characterize properly the behavior in frequency of the real falls (f_{maxPS}) or the correlation of the series corresponding to the acceleration module (μ_R).

These clear differences could be justified by the fact that fake falls ignore the main feature of real falls: their intrinsically unexpected and involuntary nature. As might be expected, these disagreements suggest that the simulated movements respond to more structured processes in which a greater acceleration is deliberately exerted to the motion by the participants and for which it is easier to detect the typical phases in which a fall (supposedly) can be discomposed. This inconsistency among the datasets can be justified by the fact that, in a simulation scenario (in which, among other circumstances, cushioning elements are normally used), the volunteers do not perform the compensatory movements aimed at reducing the damage of the accidents. These movements, present in most real falls, may instead explain some reduction in the force and speed of the impact. In turn, as these compensatory actions notably rely on the physical state of the subject and on the type of fall (much more variable in practice than those contemplated in the lab testbeds), the real falls tend to display a greater irregularity. In fact, for most of the statistics, there is a greater divergence between the FFFStudy and FARSEEING datasets than that existing between the other repositories. The use of shock-absorbing components (which clearly reduce the fear of executing rapid movements against the floor during the simulations) and the physical conditions of the participants (young people with much greater elasticity and mobility than the subjects of real falls) can also contribute to the greater energy and acceleration that are measured in the fake falls.

In any case, the FARSEEING data may be affected by their small sample number and by the fact that it includes traces captured at two different points on the body with sensors from different vendors. By the same token, when justifying the differences between the datasets, we cannot forget that the participants in the FFFStudy database present a very particular pathology (multiple sclerosis) and that in the datasets with faked falls, the age of the volunteers is far inferior to most of the fallers in the real scenarios. In any case, if these facts have an impact on the dynamics of falls, the policy of selecting young volunteers in good health for the creation of scripted evaluation datasets should also be called into question. In the aforementioned critical analysis provided by Stack in [69], the authors remarks a myriad of aspects that are normally neglected in the testbed conceived to generate mimicked falls but that may strongly affect the human dynamics: the neurological conditions (e.g. Parkinson), cognitive impairments or motor disabilities of frequent fallers or the use of walking aids. Although in some cases, participants are instructed by geriatricians or medical experts, a fall cannot be substituted by 'intentional descents' in which most postural responses and reflexive mechanisms oriented to minimize the damage (grabbing an object, arms extensions, limbs' reactions, modulation of the joints, etc.) are omitted.

Another problem is that mimicked falls normally also ignore the complex variability of causes that originate actual falls, that is to say, the pre-fall phase is not actually simulated in a realistic way. In most cases, the volunteers that emulate the falls initiate the movement from a completely static position (standing, lying on a bed, or sitting in a chair), or just pretend to collapse, slip, trip or stumble (without colliding with any real obstacle) while freely walking in a straight line. This strategy oversimplifies those situations in which the fall occurs because the subject performs more sophisticated movements (e.g. climbing stairs) or due to the unexpected interaction with some object. For example, the fall circumstances reported by some subjects in the FARSEEING dataset include cases in which the subject was hooked into a handrail while in other traces the individuals fell while picking an object or opening a door. These sudden and unpredictable interactions are not usually replicated by any of the synthetic datasets. In addition, as already mentioned, in most existing datasets the casuistry of the falls emulated in the datasets is extremely limited to a very small number of abstract 'unidirectional' movements and collapses against the ground. In the simulations, the direction of the participants while falling follows a unique direction (with three basic possibilities: forwards, backwards or lateral), which is prefixed by each scheduled experiment. In an actual fall, this direction labeling is not so simple, as compensatory movements or hitting obstacles can cause significant postural changes during the fall. The documentation provided by the authors of FARSEEING dataset describes the direction of the recorded falls following that taxonomy (forwards, lateral, backwards), although in 10 of the 22 samples this direction is documented as 'unknown', most likely due to the difficulty of cataloguing the irregular movement that the subject experienced during the fall.

Other element that is usually neglected in the production of synthetized falls is the use of assistive devices. Some of the fallers in FARSEEING dataset were walking with a wheeled walker, which obviously affect the causes, dynamics and compensatory movements of the accident. In other case in this dataset, the subject fell while standing up out of a wheelchair. However, in none of the existing synthetic datasets, the use of walkers (or wheelchairs) is contemplated.

The exact location where the fall occurs may also impact on the recorded mobility patterns. All synthetic datasets are recorded in large, clutter-free laboratory environments where any type of obstacle is removed and kept away from the experimental subjects. In contrast, real falls (especially those suffered in domestic environments) occur in much smaller spaces with walls, doors and pieces of furniture that interfere with the path of the fall movement itself (either to hit the user or to serve as a possible handhold to minimize the damage). In the FARSEEING datasets, for example, four falls took place in the toilet, a room where the mobility of users can be greatly determined by the layout of the sanitary fittings and by the presence of wet and slippery surfaces (on walls, floors, etc.). In another fall, the subject held on the wall and then slowly fell down backwards on his/her buttocks.

Table 5 summarizes the number of statistics with significantly different mean that each dataset presents with respect to the two repositories with real-world falls. The table reveals that even those datasets that include a greater number of types of falls (e.g. FallAllD, which has 38 types) do not improve the 'resemblance to reality' when compared to those datasets that simulated a reduced typology of falls.

Table 5
Number of statistical features in each dataset with emulated falls that present a significantly different mean with respect to the reference real-world fall datasets.

Dataset	FFFStudy	FARSEEING
CMDFALL (Hip)	13	4
CogentLabs (Thigh)	10	1
DLR	10	3
DOFDA	13	7
Erciyes	10	6
FallAllD	13	4
GravityPro (Thigh)	15	15
UTOL	15	14
IMUFD	15	11
KFall	14	5
MobiAct (Thigh)	13	4
SisFall	12	4
tFall (Thigh)	11	8
TST	10	3
UMAFall	11	4
UniMiB (Thigh)	12	10
UPFall	9	3
UR	10	6

These results are coherent with the conclusions of other previous studies, such as that provided by Hu et al. in [46], where authors highlight that the SMV and SMA computed for the acceleration in real falls of older adults are much smaller than those calculated for falls mimicked by young and healthy individuals.

Kangas et al. stated in [60] that real-life forward falls, sideway falls and backward falls have similar features to those from simulated falls. As already commented, authors compared the signals from five real falls of older adults and the averaged signals from a set of falls of different types simulated by 20 middle-aged volunteer subjects on a soft mattress. However, the comparison was mainly grounded on the visual inspection of the acceleration magnitude captured at the waist during the falls. From this visual analysis, authors conclude that the evolution of the acceleration in real and 'fake' falls looked similar and showed a pre-impact and an impact phase. Bourke et al. also affirmed in [128] that the acceleration provoked by real falls (around the impact) do exhibit the same 'contour' seen from young 'fake' fallers. However, the prototypical pattern of the acceleration magnitude of a fall, consisting of sudden decay to zero followed by a single clear peak and a period of quietness is not always present in real falls. In [33], Huq et al. offer a basic visual analysis of the evolution of the acceleration pattern of four real world falls (captured after tracking the mobility of 29 older adults with the accelerometer embedded in a smartphone). The visual inspection confirms the irregular nature of falls as the acceleration peaks do not always coincide with the impact against the floor. In other cases, falls may provoke multiple peaks. For example, in 9 out of the 22 falls collected in the FAARSEING project, fallers declare that they were hit by certain object before the collapse [11].

After a brief comparison of FFFStudy and SisFall datasets, authors in [36] have also shown that the acceleration magnitude of real and 'fake' falls differ in the three basic stages of the accident: the pre-impact, impact and post-impact phases. In particular, artificial falls entail a more violent impact (a higher value of SMV) while the same variable present lower values in the periods before and after the impacts. This fact may indicate that volunteers do not simulate properly either the abnormal movements caused by the instability before the fall or the actions (for example, the possible attempts to get up or settle on the ground) after the impact.

This variability and lack of common mobility pattern is clearly present in FARSEEING and FFFStudy datasets. To illustrate this behavior, Fig. 1 depicts the evolution of the acceleration magnitude in four

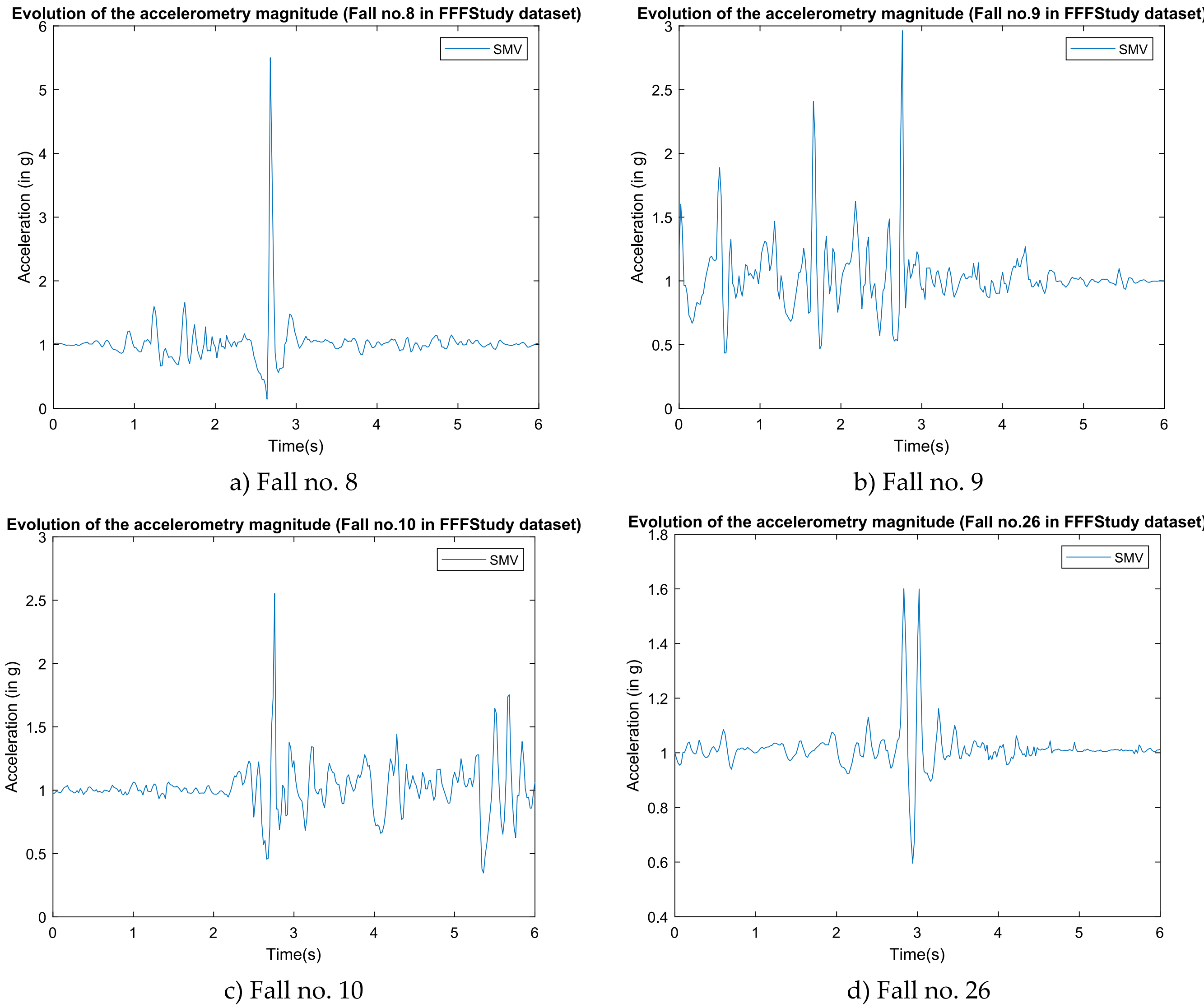

Fig. 1. Evolution of the acceleration magnitude during four falls of FFFStudy dataset.

different falls contained in the FFFStudy dataset. Unfortunately, the authors of the FFFStudy dataset do not provide details on the circumstances (typology, previous movements, consequences, final position of the subject or possible recovery of the upright position, etc.) of the falls included in this repository. However, the graphs in this figure evince the high mutability of the dynamics of real falls, which are far from reproducing a common and easily identifiable evolution. Thus, some falls (such as that in graph (a)) present the typical fall phases presumed by the literature but, in other cases, strong secondary acceleration peaks (graph (d)) may be easily confused with the impact against the floor, while in other falls, a high activity (with strong acceleration variation) alternatively precedes (graph (b)) or follows (graph (c)) the impact. This changeable nature of the dynamics of real falls contrasts with the reduced number of types and rigid execution of the falls emulated to generate those 'synthetic' repositories that are massively considered in the research on FDSs.

As it refers to the timing and duration of falls, the idea that real falls are usually less brusque than simulated ones is not new either, although it is normally not considered in the design of evaluation frameworks for FDSs. To cope with this problem, authors in [129] introduce in their evaluation a new type of simulated fall (fall against a wall). For this purpose, during the execution of the movement, the participant contacts the wall for support before slipping down slowly to the ground until adopting a sitting position. Though, this type of fall patterns is uncommon in the available datasets.

Figs. 2 and 3 respectively illustrate the boxplots of the maximum (SMV_{max}) and minimum acceleration (SMV_{min}) magnitude values for the fall movements of all datasets under examination. In the graphs, the central red line in each box indicates the median of the related statistic, while the lower and upper limits of the box represent the 25th and 75th percentiles of the data distribution. The dotted lines, sometimes known as 'whiskers,' denote a 1.5 IQR (Interquartile Range between the 25th and 75th percentiles) interval above and below the box. Outliers are defined as data outside these boundaries (box and whiskers) and are tagged with red crosses in the figures. The name of the dataset is accompanied by the position if the sensor (Th -Thigh- or Hip) when the traces were not collected on the waist. The graphs show anomalies in the statistics of two datasets (Gravity Project and, above all, UTOL), which exhibit -for example- very small acceleration peaks for the fall movements. This anomalous behavior could be due to the fact that the continuous component of 1 g caused by gravity was removed from the acceleration samples before they were recorded. In any case, the corresponding works that describe these datasets do not report any type of pre-processing. On the other hand, the Gravity Project dataset presents a very low number of samples (only 45 ADLs and 72 falls) while in the case of the UTOL repository the falls were simulated in an unconventional

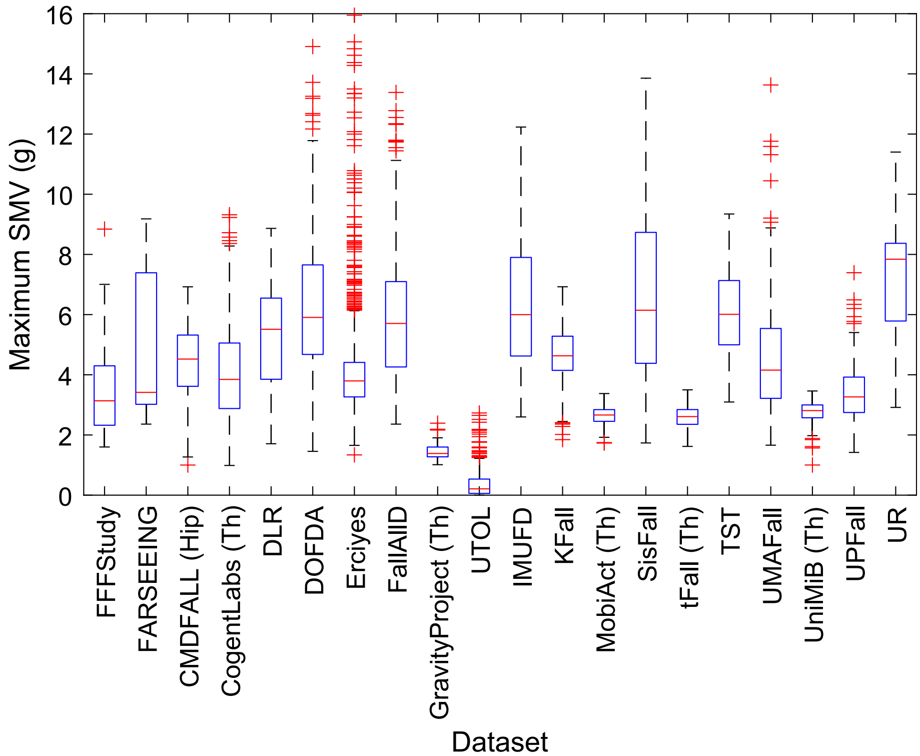

Fig. 2. Boxplots of the maximum (SMV_{max}) of the SMV for the falls in all datasets.

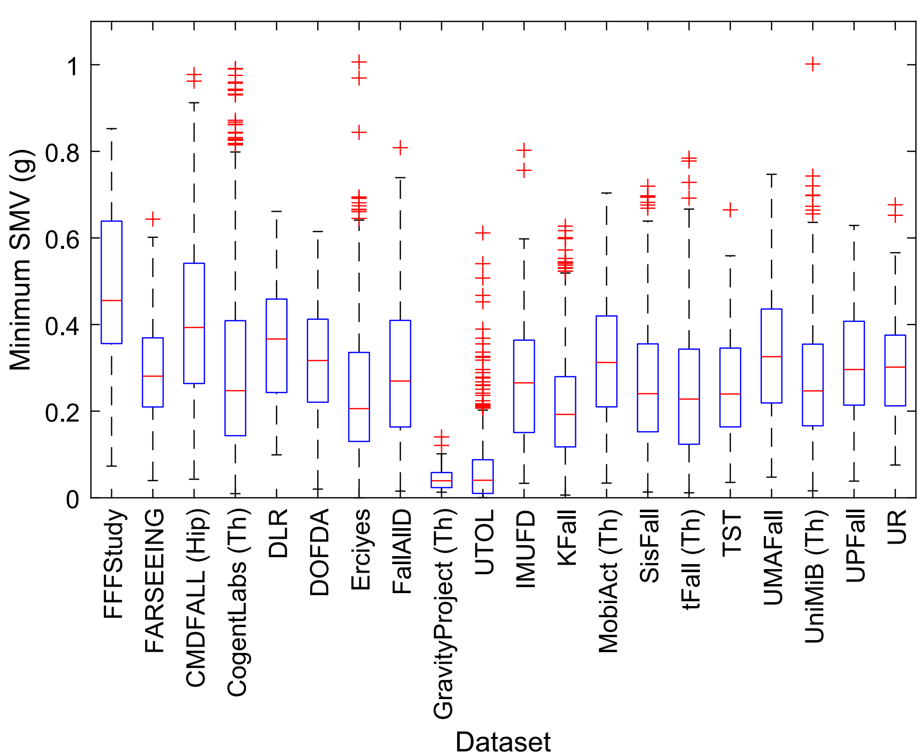

Fig. 3. Boxplots of the minimum (SMV_{min}) of the SMV for the falls in all datasets.

and unusual way (by five martial artists performing in parallel) and monitored with a extremely low sampling rate (5 Hz). Perhaps due to these facts, both databases are not very representative of the datasets typically considered by the research on FDSs and have been scarcely employed by the related literature on acceleration-based detectors.

Figs. 2 and 3 confirm the conclusions achieved with the analysis of the mean values of the same statistics: when compared with most datasets with simulated movements, real falls (in particular those provided by FFFStudy dataset) present a smoother behavior than that of the mimicked falls. This is reflected in lower acceleration peaks due to the impact against the floor and a less sharp drop of the acceleration magnitude during the free-fall periods.

Fig. 2 shows that the emulated falls of certain datasets (such as UniMiB, tFall or Mobiact) apparently exhibit lower acceleration peaks than real falls. However, as it can be deduced from the boxplots in the figure, the measurements in these datasets are visibly restrained by the low range of the sensor (±2 g) for each acceleration component. This range is unable to properly measure values of the acceleration magnitude higher than 3.46 g. Thus, those falls involving strong impacts against the floor provoke the saturation of the sensor and cannot be adequately characterized with the accelerometer. This limitation in the sensor range (which is not always taken into account by the related literature when benchmarking the detection algorithms) should discourage the use of these datasets.

Fig. 4 (for SMV_{max}) and Fig. 5 (for SMV_{min}) also depict the distribution of these features although, in this case, for the datasets generated in the laboratory, the analyzed samples correspond to the ADLs while for FFFStudy and FARSEEING datasets (which do not contain ADLs), the boxplots again correspond to those previously calculated from the actual falls. The visual comparisons of Figs. 2 and 4 and Figs. 3 and 5 shows that the divergences between actual and simulated falls are not more relevant or evident than that existing between actual falls and ADLs. Thus, the boxplots of both statistics for real and simulated falls do not overlap in a more significant way than the boxplots of the same characteristics for the real falls and the ADLs of the 'synthetic' datasets.

According to the simple analysis of these two basic statistics (which describe the acceleration valleys and peaks caused by the falls) the separation between the fake falls and the ADLs of the synthetic datasets is much higher than that really present between the real falls and the daily life movements. A similar behavior (not shown here) is reported for the other statistics. This could explain why, as demonstrated in the literature review presented in the introduction, a detector trained or designed with emulated falls offers such a poor performance when tested in a real scenario of constant monitoring.

These findings confirm the inadequacy (already suggested by other authors) of designing and evaluating algorithms for wearable FDSs with simulated falls. In the case of employing simple threshold-oriented strategies, the selection of the values of the thresholds based on data collected on simulations (for example, for the detection of the peak caused by impacting the ground) probably leads, in a real scenario, to very low sensitivity rates. Similarly, the use of more sophisticated techniques, by means of trained machine learning or deep learning models, may entail the over-learning of well-defined simulated fall signals, with features derived from unrealistic dynamics that cannot be extrapolated to the more varied mobility patterns exhibited by real-world falls. Moreover, the notable variability in the nature of the falls shown by the characterization of the acceleration signals calls into question the very fact that all falls can be unambiguously identified from the simple examination of the accelerometric measurements. In this regard, in some wearable detectors proposed in the literature, it has been suggested to analyze the global orientation change of the body as a detection criterion (by comparing the direction of the acceleration vector components before and after the fall). This evaluation procedure is difficult to apply and evaluate with emulated falls since it heavily depends on the final posture that the participant decides to adopt after the collapse. However, if this criterion is used with real falls, it is not a decisive parameter either. To prove this point, Fig. 6 depicts the histogram of the rotation angle provoked by the reals falls in the acceleration components. The angles in this histogram (which combines the falls from both FARSEEING and FFFStudy datasets) are computed between the mean acceleration vectors before and after the fall (calculated from the first and last five seconds of the 100 s intervals where the falls take place). The figure shows that many falls cause a clear modification (higher than 40°) of the orientation of the subject's body but in a not negligible number of cases, this change is not so remarkable. Thus, this long-standing variation of the body cannot even be used as a decisive condition to determine if a fall has occurred. A similar conclusion is achieved by Bourke et al. in [128] after examining FARSEEING datasets.

With that in mind, Mosquera-López et al. (who authored the FFFStudy dataset) have shown that the specificity [36] may improve when the detector is inputted not only with acceleration measurements but also with contextual information (user localization). In this respect,

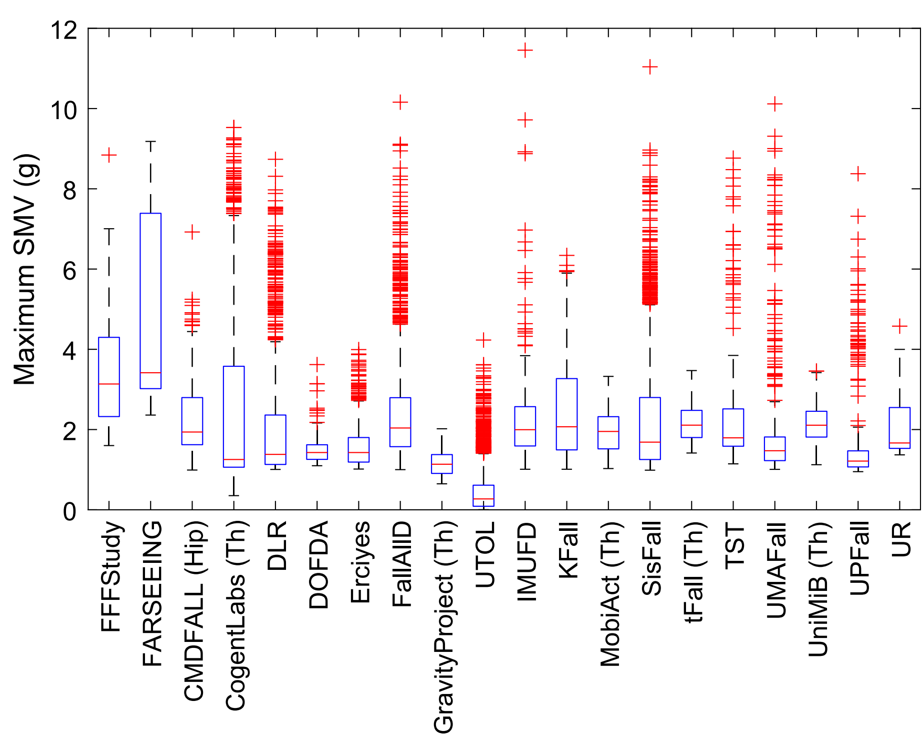

Fig. 4. Boxplots of the maximum (SMV_{max}) of the SMV of the actual falls (in FFFStudy and FARSEEING datasets) and of the ADLs in the rest of benchmarking datasets.

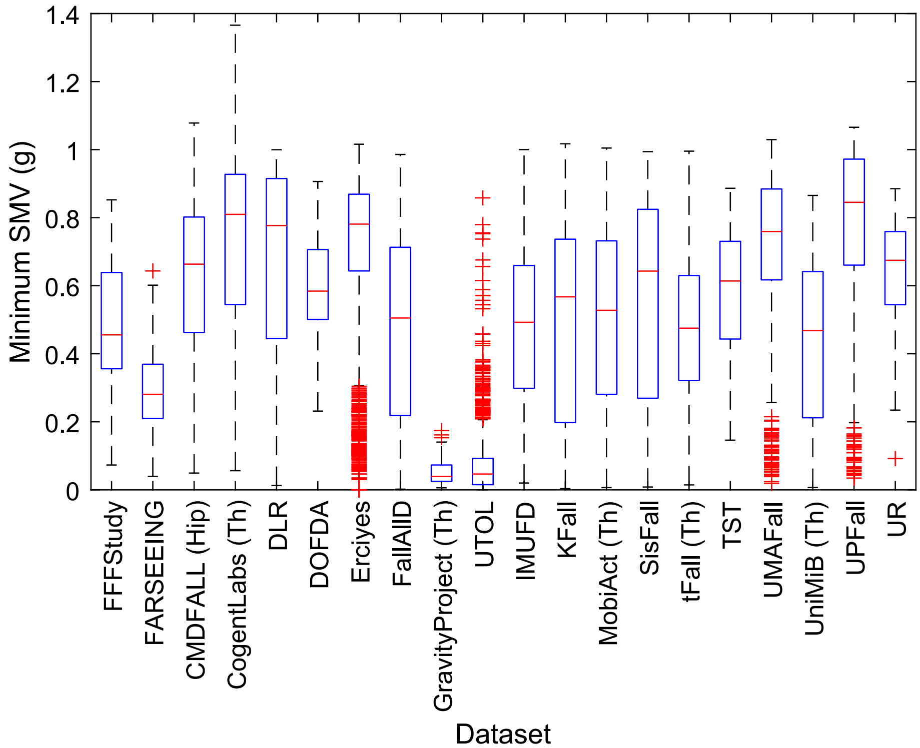

Fig. 5. Boxplots of the minimum (SMV_{min}) of the SMV of the actual falls (in FFFStudy and FARSEEING datasets) and of the ADLs in the rest of benchmarking datasets.

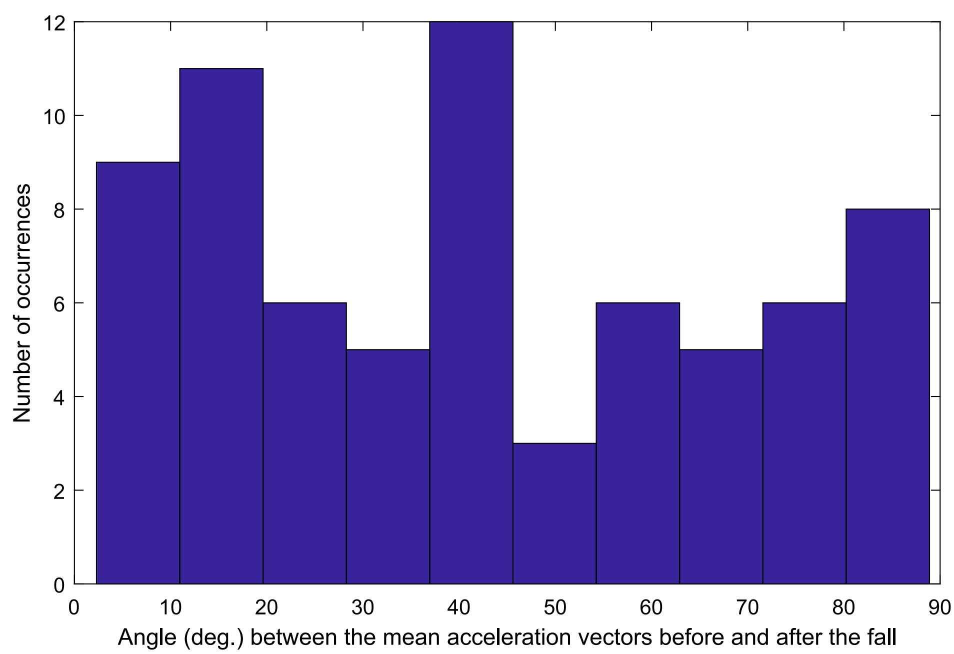

Fig. 6. Histogram of the rotation angle provoked in the acceleration by the falls (FFFStudy&FARSEEING datasets).

the problem of fall detection under realistic conditions should be addressed from a sensor-fusion perspective. We think that the current tendency [130131] to design multi-sensor-fusion wearable FDSs, based on the coordinated study of several sensors (including variables other than inertial signals, such as heart rate) or the hybridization with contextual systems are heading in the right direction to make fall detectors an effective technology in real application scenarios.

The performed study is certainly limited by the sample size in the two databases that contain inertial measurements of real falls (the only ones publicly available to date -to the best of our knowledge-). Besides, the results may be also largely determined by the number and medical conditions of the subjects employed in these repositories. If new datasets generated by long-term monitoring of fall-prone subjects appear in the near future, the analysis should be repeated to corroborate the universality of these conclusions with new databases. In addition, the results could also be affected by certain operational factors that parameterize the testbeds in which the samples were captured, as this procedure differs significantly from one dataset to another. Although certain studies have revealed that a frequency greater than 15 Hz is sufficient to characterize the mobility of falls [132], the sampling frequency (which is higher than that value for all the used datasets except one -the aforementioned UTOL-) could influence the statistics derived from some of the datasets (whose computation has required a re-sampling of the measurement series for some repositories). Likewise, an incorrect calibration of the sensors or the particular placement and orientation of the sensing nodes on the waist (used in each testbed) may introduce some bias in the statistics. Future studies should analyze in detail the actual importance of these factors.

In any case, the obtained results suggest that the evaluation procedure commonly followed by the literature should be revised. In this regard we suggest a twofold basic mechanism to evaluate fall detection algorithms:

1. Firstly, with independence of the trace used to configure or train the classifiers, the detectors should be tested against those available datasets that include real falls, as an initial method to assess its capacity to identify actual fall patterns.
2. Secondly, the detection algorithms should be implemented on actual wearables so that their effectiveness can be tested in real (or realistic) conditions through long-term monitoring campaigns with target users (e.g. older adults) during their daily routines. If during these experiments in real scenarios, the subjects do not experience any falls, at least the test will serve to quantify the rate of false alarms that the detector generates (an aspect that is as important as the sensitivity when determining the actual feasibility of this alerting system as a telecare service).

5. Conclusions

Due to the logistical and operational difficulties of collecting real falls, the literature on wearable fall detection systems evaluate their proposals mainly by means of databases generated by volunteers who simulate falling on padded surfaces. Aiming at examining the validity of this evaluation procedure, this study has presented a detailed comparison of the acceleration signals recorded during real falls (available in two public databases) with those gathered through emulated falls and offered by different repositories which are commonly used by the related literature. In particular, 15 statistics or descriptors of the physical activity have been computed from the triaxial components of the acceleration measured during the short time interval (2 s) that precedes and follows the impact against the ground.

As previous studies had suggested, the results confirm the great divergence between ‘fake’ and real falls, since most of the considered descriptors present means with statistically significant differences for all the existing datasets. In general, human mobility in actual falls offers a less violent and abrupt behavior than that caused by the mimicked ones. This fact is reflected in less noticeable values for a group of parameters (e.g. the minimum or maximum acceleration magnitude, the average acceleration, the signal magnitude area, the energy, or changes in acceleration or signal energy) as well as in smaller intervals of the period of free fall or of the time between the minimum (final instant of the free fall phase) and the maximum (impact) acceleration magnitudes. As a matter of fact, for a notable number of features derived from the acceleration, many real falls can even exhibit a behavior more similar to that of the ADLs existing in the datasets obtained in laboratories than that estimated from the simulated falls contained in the same databases.

The participants recruited for the testbeds created to generate ‘synthetic’ datasets normally execute predefined, highly ‘structured’ movements that do not respond to the varied and spontaneous imbalances that typically cause real life falls. Furthermore, during a simulated fall (generally performed on a cushioning element), volunteers tend to reduce or eliminate the compensatory movements aimed at minimizing the damage of the accident, which obviously alters the realism of the simulations. Similarly, the irregularity and unpredictability of the fall provokes that the databases with real falls present a greater intervariability than that existing between the 'synthetic' datasets themselves. The typology of the monitored users (age, physical conditions, previous pathologies, disabilities, etc.), the variety of the causes (slips, stumbles, tripping hazards, etc.) and the location of the accident (domestic, outdoors) may also introduce a considerable variability in the dynamics of real falls, which is not adequately represented in the repositories with simulations, which are executed by young and healthy volunteers in laboratory conditions and in circumstances very abstracted from the contingencies and immediate experience of real-world falls.

These findings largely discredit the evaluation strategy (based on datasets generated through programmed movements) massively followed by the literature. The fact is that clinical tests (documented to date) of fall detectors carried out in scenarios of real and continuous monitoring of vulnerable people (elderly or patients with certain disabilities) unanimously show a clear underperformance of the FDSs with respect to the results obtained by detection algorithms that were trained and evaluated with datasets generated in the laboratory. Research on FDSs should reframe the problem of evaluation, which should be reoriented towards long-term tests in realistic scenarios and with participants recruited from the end users at whom these systems are really targeted. Likewise, from the study, it is possible to infer the inconvenience of basing the fall detection algorithms uniquely on the scrutiny of inertial signals (in particular, acceleration), as it is proposed in most works on wearable FDSs. As has been shown in recent articles, the development of efficient FDSs most surely requires a multi-sensor perspective in which the detection algorithm must found its decision on the simultaneous and coordinated analysis of a heterogeneous set of user’s signals (location, biosignals, etc.).

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CRediT authorship contribution statement

Eduardo Casilari: Conceptualization, Software, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Supervision, Validation, Writing – original draft, Writing – review & editing. **Carlos A. Silva:** Supervision, Validation, Software, Visualization, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The study is based on publicly available datasets

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