Fall Detection Combining Android Accelerometer and Step Counting Virtual Sensors

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Abstract. INTRODUCTION: Falls constitute a significant threat to older adults. Several approaches aimed at automatically detecting falls exist. Smartphones are widespread and can serve as a low-cost pervasive platform for automated fall detection. Existing fall detection apps are highly sensitive, but often suffers from sub-optimal specificity which can result in many false positives.

OBJECTIVES: The aim of this study was to investigate whether the built-in pedometer virtual sensor on the Android smartphone platform can be used to increase specificity and thereby achieve higher accuracy in an accelerometer-based Android fall detection application.

METHODS: An existing open threshold-based accelerometer algorithm was combined with the standard Android virtual sensor pedometer algorithm for detecting walking in the postfall phase. In a range of experiments, falls were simulated using a combination of a test mannequin and test participants, in order to determine the sensitivity and specificity of the solution.

RESULTS: All simulated falls were detected with 100% sensitivity. By counting postfall subsequent steps using the Android pedometer virtual sensor, the specificity of the application was increased to 100% in all scenarios.

CONCLUSION: The combination of accelerometer and pedometer sensors was found feasible to use for increasing the specificity of existing open fall detection algorithms.

Keywords: Fall detection · Smart phone · Accelerometer · Pedometer

1 Introduction

The ageing of the world's population is becoming one of the most significant social transformations of our time [1]. The number of people aged 65 years or above is projected to grow from nine percent in 2019 to nearly 12% in 2030. The number of people aged 80 years or over is expected to be nearly tripled by 2050 [2].

G. A. Papadopoulos et al. (Eds.): IHAW 2022, CCIS 1799, pp. 3–16, 2023.
https://doi.org/10.1007/978-3-031-29548-5_1

Based on these demographic changes, many countries are adopting healthy ageing policies to help elderly living an active and independent life [3].

Age is one of the key risk factors for fall accidents, and elderly people are the most exposed. Each year, more than 30% of people above the age of 65 falls, and in half of the cases, falls are recurrent [4].

In a systematic review of fall definitions and measuring methods, some of the adjectives to describe falls are 'unintentional', 'unexpected', 'sudden' and 'unplanned' which all state an element of surprise for the participant. Two common definitions are from the WHO (i) and the Kellogg Group (ii) [5–7].

(i) A fall is defined as an event which results in a person coming to rest inadvertently on the ground or floor or other lower level.
(ii) A fall is an event which results in a person coming to rest inadvertently on the ground or other lower level and other than as a consequence of the following: sustaining a violent blow, loss of consciousness, sudden onset of paralysis, as in a stroke, an epileptic seizure.

Falls have been proven to have a high correlation with mortality, morbidity, functionality and premature nursing home admissions [8,9].

Some of the health-related consequences include fractures, soft tissue injuries, longstanding pain and functional impairment which lead to reduced quality of life [10].

In a study by Bergland et al., 51% of the falls resulted in an injury, of which 24% were considered severe. Thirteen percent of the falls resulted in fractures. The researchers further suggest that the inability to get up from the floor was the most influential risk factor for fall-related severe injuries [11].

According to the report, *How dangerous are falls in old people at home?*, 50% of those who were lying on the floor longer than one hour died within the following six months [12]. Fleming et al. investigated fall reports and found that in 54% of the cases, the individual was found on the floor. Of the 60% involved individuals, 80% of the participants were unable to get up from the floor, and 30% had lain on the floor for at least one hour. A lie of one hour or more is often referred to as a "long lie" [13–15].

The impact of long lies is the motivation behind automated information and communication technology systems which can detect and react to the actual fall event occurring. The main objective of an automated fall detection system is to automatically detect when a fall event has occurred. Fall detection systems seek to discriminate between fall events and activity of daily living (ADL) events. This is challenging as some ADL events, like sitting down from a standing position in a chair or on a bed, or running or walking at high speeds, have similarities to falls which often results in lower specificity of the fall detection system. Robust fall detectors have the potential to detect the falls early and avoid the severe consequences of long lies while avoiding false positives. To summarize, falls that go undetected increases suffering and the risk of more severe infections and death, while an excessive number of false alarms can lead to economic loss and caregivers rejecting the system [16]. Studies have investigated a

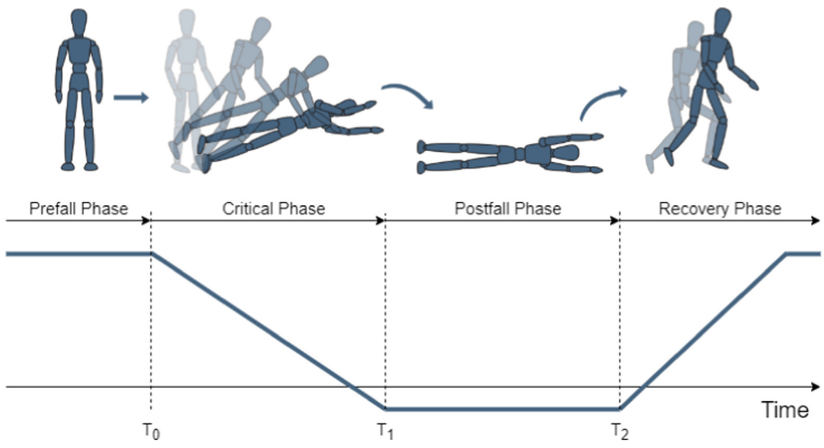

Fig. 1. A fall divided into the phases proposed by Noury et al. Source: Own work.

variety of approaches, including cameras, ambient sensors and wearable devices such as smartphones and smartwatches with mixed results [16].

Noury et al. proposed protocols for the evaluation of fall detection algorithms. For categorising the algorithms, they divide falls into four phases: the prefall phase, the critical phase, the postfall phase and the recovery phase. Figure 1 illustrates the phases based on the proposed protocol. In the prefall phase, the person performs the usual ADL where sudden movements that should be distinguished from a fall may happen. In the critical phase, the person is subject to a sudden movement of the body toward the ground with a small (T_1–T_0 = 300–500 ms) duration ending in a fall. In the postfall phase, the person is lying on the floor inactively, and this phase should preferably not last longer than an hour (T_2–T_1 < 1h). The recovery phase consists of the person getting up from the floor on his own or with help [17].

2 Related Work

Fall detection systems can be grouped into camera-based, ambient device-based, wearable device-based and sensor fusion-based systems [18,19].

Ambient device-based systems often consist of a variety of sensors which are deployed in the environment. This means that the subject does not need to wear a device. However, the system is limited to the placement of the sensors, whereas the most common are floor sensors, microphones and pressure sensors [16].

Camera-based systems typically consist of a video camera monitoring the home of the elderly in combination with computer vision algorithms which can detect falls based on the video feed [20]. In a review from 2013, the included camera-based systems started with an object detection followed by feature extraction to have sufficient discriminative power to identify fall events. Ultimately, a large variety of different classifiers were used to determine the fall event [16].

Wearable devices are worn by the person as accessories, embedded in clothing, implanted in the user's body or even tattooed on the skin [21]. The majority of fall detection systems within this area use accelerometer sensors while some incorporate other sensor types such as gyroscopes [16].

Sensor fusion combines multiple physical sensors to achieve higher accuracy than the individual sensors are capable of [22].

2.1 Accelerometer-Based Devices

Accelerometer-based devices are a subgroup of wearable devices and are a major area for detection of the critical phase of a fall [16]. Igual et al. groups accelerometer-based systems into two categories [16]:

(i) Threshold-based method (TBM) where a fall is reported when the acceleration peaks, valleys or exceeds predefined thresholds
(ii) Machine learning-based method (MLM) which uses machine learning techniques to classify and report a fall

In 2005, Lindemann et al. integrated an accelerometer-based fall detector into a hearing aid-housing which was fixed behind the ear. The TBM achieved 100% sensitivity and a self-stated "high" specificity [23].

Also, Bourke et al. explored a TBM with a tri-axial accelerometer for fall detection. With both young and elderly subjects, the authors investigated the ability to discriminate between falls and ADLand achieved a specificity of 83.3–100% [24].

Li et al. based a system on accelerometers and gyroscopes, which sought to recognise static postures and the dynamic transitions between the postures where fall is an unintentional transition to a lying state [25].

Kerdegari et al. used an MLM and classified acceleration data using 6,962 instances and 29 attributes with different machine learning algorithms. Multilayer perceptron classified 90.15% of the instances correctly where the primitive learning scheme ZeroR managed to classify 66.49% correctly [26].

Özdemir investigated the optimal sensor placement of accelerometer, gyroscope and magnetometer sensors by combing 378 combinations of sensor placements and machine learning techniques. They concluded that the best sensitivity was accomplished with sensors being placed in the waist region with 99.96% sensitivity and 99.76% specificity although the wrist is highly preferred for today's wearable applications and achieved 94.92% accuracy [27]. Ntanasis et al. reached the same conclusion and also highlighted the thigh as an optimal location [28].

Kangas et al. tested different body placements for a 3-axis accelerometer sensor with different types of falls, including forward, backward and lateral fall directions. The authors concluded that an accelerometer placed on the waist or the head achieved 97–98% sensitivity and 100% specificity, and concluded that a simple algorithm is sufficient in these cases [29].

2.2 Smartphone-Systems

While most sensors tend to introduce additional objects in the homes of the elderly, many elderly people already own a smartphone [30].

In 2018, it was reported that 73% of people between 65–74 years and 42% between 75–89 years in Denmark possessed a smartphone, and most of them used it for internet access [31]. Emergency calls and alarms were some of the most attractive potentials of cell phones for the elderly people who were often more likely to see the phone as a safety device opposed to seeing it as a social communication device [32,33]. Due to widespread availability and decreasing prices for smartphones, the number of smartphone-based fall detection approaches has increased in the literature, while the number of prototypes based on special-purpose hardware has decreased [30]. These properties come with evident advantages. Smartphone applications can operate almost everywhere because of the availability, and most current smartphones already integrate not only the required hardware in terms of accelerometers and gyroscopes but also cameras, microphones, digital compasses and GPS units [34].

Zhuang et al. compared different mobile operating systems for a fall detection application, including Windows Phone, Symbian, and Android and decided to use Android due to its multitasking capabilities and accessible integration to the system components which led to decreased implementation efforts [35]. In 2010, Dai et al. proposed *PerFallD* as, according to themselves, the first pervasive fall detection system utilising mobile phones as the platform. The authors implemented a prototype on an Android G1 phone, which considered the values of the total acceleration of the phone and the absolute vertical acceleration during a time window. The performance of the prototype was evaluated with both a mannequin and test participants. It was afterwards compared with existing solutions. Using a TBM with 15 test participants, the prototype achieved an average sensitivity of 91.3% and an average specificity of 97.3% while also highlighting the waist as the optimal position. When using a mannequin, the results showed a slightly lower specificity of 97.2% [36].

He et al. used the same approach and classified body motions into five different patterns, i.e. vertical activity, lying, sitting or static standing, horizontal activity and fall. The authors found it to be a problem that the smartphone was worn in the pocket rather than attached on the waist because its loose attachment in the pocket might introduce mechanical movement [37].

Tran et al. used machine learning techniques to classify falls by implementing a self-learning mechanism with user interactions to avoid false alarms. The prototype was tested with 92 volunteering students who performed four activities: sitting, jumping, walking and falling. The authors concluded that the experiments yielded better results in terms of accuracy than the most downloaded commercial applications with a sensitivity of 60.5% and a specificity of 94.8% [38].

3 Scope and Objectives

As shown, there is a large body of existing work on creating fall detection algorithms using smartphones. This includes freely available existing open fall detection algorithms as well as studies on using the Android platform on a smartphone to execute these algorithms [29]. However, to the best of our knowledge, our study is the first to investigate the potential of combining existing open fall detection algorithms, running on a standard Android smartphone combined with step counting of the user measured by the built-in virtual sensor pedometer of the Android platform in order to lower the false positive rate and thereby increase the specificity of the system. In addition, no open source fall detection apps for Android was found in our related work survey. Open source can be important if the service is to be used as part of a greater ecosystem of sensors and services, rather than as a stand-alone app.

The aim of this study was to investigate whether the built-in pedometer virtual sensor on the Android smartphone platform can be used to increase specificity and thereby achieve higher accuracy in an accelerometer-based Android fall detection application.

4 Materials and Methods

The study uses the Java programming language to build an Android "fall detector evaluation app" in order to facilitate our experiments. The app utilized two of the Android platform's virtual sensors: The "Accelerometer sensor" and the "Step counting sensor".

In order to mitigate "device bias", two typical Android phones were used simultaneously during all experiment: The Google Pixel 4, Google, US and the Nexus 5X, LG, South Korea.

The fall detection evaluation app detects fall events by combining sensor data from the accelerometer and the pedometer sensors. Initially, the application detects a fall motion followed by monitoring the user's steps. If steps are detected subsequently, the fall motion is discarded. However, if no steps are detected within a given grace period, the fall motion will be identified as a fall event and thus be reported.

The detection of fall motions are based on the paper *Comparison of low-complexity fall detection algorithms for body attached accelerometers* that proposed three low-complexity fall detection algorithms for body attached accelerometers. All three algorithms are threshold based and combine the identification of drop, impact, posture and velocity in different ways to detect fall events [29].

The fall detection algorithm in our study implements one of these accelerometer-based approaches to identify a drop and the subsequent impact to detect fall motions. The magnitude of a "resultant vector" (RV) is calculated based on the acceleration force data from the three coordinate axes as shown in Eq. (1) where x, y and z are the acceleration in the x-, y-, and z-planes, respectively.

$$|\mathrm{RV}| = \sqrt{x^2 + y^2 + z^2} \tag{1}$$

When the phone is in a stationary position, the magnitude of the RV is approximately 1 g, and when the phone is in free fall, the RV has a magnitude of 0 g. Since RV is the summation of the accelerations in all three dimensions, the orientation of the phone has no impact on the result. A drop is identified when the magnitude of RV gets below 0.6 g, and an impact is identified when the magnitude is higher than 2.0 g. A fall motion is detected, when a drop occurs, followed by an impact within one second.

To investigate the performance of the fall detection application when combining pedometer and accelerometer data, five test scenarios were defined (S1–S5).

Scenario S1 and S2 investigated whether the algorithm could detect the fall event correctly based on the postfall phase. Simulated falls were performed using a test mannequin, as it is not considered ethical to use human participants due to the risk of potential injury during the fall. The mannequin consisted of a body based on 60 kg boxing bag with an attached plastic head. Running the research application, both Android smartphones were placed in the two pockets of the pullover. In both scenarios, the authors manoeuvred the mannequin according to the scenarios' respective protocols.

Scenarios S3, S4 and S5 studied selected misclassifications of fall motions during ADL events. In these scenarios, human test participants were used rather than the mannequin, as there were no risks associated with these scenarios.

In scenarios S3 to S5, participants carried the smartphones with the test software installed, one in each front pocket, while performing the procedures. The chair used in scenarios S3 and S5 was 47 cm from the floor to the seat and cushioned. In scenario S4, a bed with a height of 43 cm from the floor to the top of the mattress was used.
The specific protocol of the scenarios S1-S5 were:

S1: Simulated fall using test mannequin without recovery in the postfall phase, where the test mannequin remains lying on the ground.
S2: Simulated fall using test mannequin followed by a recovery phase, where the test mannequin is able to recover immediately after a fall and continues walking where the mannequin is picked up and carried by a facilitator.
S3: Sitting down in chair scenario. Test participant sits down on a chair in order to test the prevalence of false positive fall events during this type of activity.
S4: Lying down in bed scenario. The participant lies down on a bed in order to test the prevalence of false positive fall events during this type activity.
S5: Rising up from chair scenario. The participant rises from a chair in order to test the prevalence of false positive fall events during this type of activity.

5 Results

The group of participants consisted of two male and two female subjects, aged 25, 29, 56 and 64 years. Authors acted as test facilitators.

Table 1 presents the results from scenario S1, where a true positive is representing the algorithm detecting a fall event, and a false negative represents the cases where it did not detect a fall event.

Table 1. Results of scenario S1 which show the sensitivity of the fall detection algorithm on two Android smartphones, the Nexus 5X from LG and the Pixel 5 from Google. For all scenarios, 100% sensitivity was secured.

Scenario	Specificity	Model	True Positive	False Negative
S1	100%	Pixel	7	0
S1	100%	Nexus 5X	7	0
S1	100%	Total	14	0

Table 2 presents the results for scenarios S2 to S5. A true negative was registered when no fall events were detected, and a false positive was registered when a fall event was detected.

Table 2. Results of scenarios S2–S5, showing the specificity of the fall detection algorithm on a Nexus 5X, LG and a Pixel 5, Google. For all scenarios, 100% sensitivity was secured.

Scenario	Specificity	Model	True Positive	False Negative
S2	100%	Pixel	7	0
	100%	Nexus 5X	7	0
	Total		14	0
S3	97.5%	Pixel	38	2
	96.25%	Nexus 5X	39	1
	Total		77	3
S4	90%	Pixel	35	5
	88.5%	Nexus 5X	36	4
	Total		71	9
S5	100%	Pixel	40	0
	100%	Nexus 5X	40	0
	Total		80	0

6 Discussion

As seen in Table 1, the algorithm achieved a sensitivity of 100% in all test cases in scenario S1, which means that it was capable of classifying all falls correctly. Both smartphones returned the same outcome of 0 false negatives. At first glance, it is positive that the algorithm is capable of detecting all falls, but it may also indicate that it is hypersensitive, because the threshold is set too low. A low threshold can lead to a high number of false positives. However, one could argue that this is suitable for the use scenarios, as false positives should be sorted out by looking at subsequent events in the postfall and recovery phases.

The high sensitivity may also be related to the use of a mannequin which can lead to a significantly higher impact. In real-life scenarios, more diverse falls are to be expected, which may go undetected and thus result in a lower sensitivity.

The results from the scenarios S2, S3, S4, and S5 are shown in Table 2. Scenario S2 achieved 100% specificity for all test cases which means that if minimum seven subsequent steps are detected within the given period, which can span from 30 to 90 s after a fall motion detection, the algorithm is able to discard the fall motion as a false positive. Due to implementation details, the non-deterministic timespan can affect the reproducibility in a negative direction.

The high specificity of our study is likely associated with the limited number of scenarios selected. Preferably, a broader range of activities should be investigated in future studies.

Scenarios S3, S4, and S5 achieved more diverse results than S1 and S2. The algorithm was able to correctly discriminate between a fall and standing up from a chair with 100% specificity. S3 achieved a total specificity of 96.25% with just one false positive on the Nexus 5X. S4 also shows promising results that span from 87.5% specificity on the Pixel phone to 90% specificity on the Nexus 5X. These results show high performance in discriminating between falls and sitting and lying down. However, when a person is sitting or lying down, it is appropriate to assume that subsequent steps will be absent. This can be due to the fact that the user is not moving, but also that the smartphone may be placed in a stationary position. These situations can potentially lead to a false-positive fall detection in the fall detection algorithm.

The specificity may also be affected by the diversity amongst the test participants. In scenarios S3, S4 and S5, a non-homogeneous group of participants with differences in age, gender, weight, and height were recruited. The results may express that the algorithm does not suit all individuals. However, no correlation could be found between the individual test subjects and false positives.

The first scenario S1 evaluated the sensitivity of the fall detection algorithm on the Android application by placing a smartphone on the upper body region of the mannequin. The mannequin was held in an upright position followed by a backward free fall with no subsequent movement. The use of a mannequin comes with the significant advantage that a fall can be performed without restrictions to avoid injuries to human test participants. However, one disadvantage is that a mannequin does not perform actions like injury-avoiding initiatives during the falls, which can make the impact higher than if a human was falling. This could potentially lead to a higher sensitivity compared to a real-world scenario. Thus, the algorithm threshold in the implemented TBM is more likely to be exceeded and produce a fall event. The use of a mannequin makes the experiments reproducible as the same specific mannequin can be used to replicate experiments multiple times.

Alwan et al. also used an anthropomorphic mannequin with similar mass and mass distribution to a human to perform falls from an upright position and while attempting to get out of a wheelchair. The authors obtained a high accuracy of 100%, which strengthens the hypothesis that the use of mannequins could lead to higher sensitivity [39]. The study by Alwan et al. detected falls based on floor vibrations and is thus also subject to the high impact with the use of a mannequin which makes the study comparable to our study. Optimally, we would use real-world fall data which could lead to a decreased sensitivity.

Also, the threshold should be tested with persons of different genders, ages, weights, heights and with different fall histories and assistive devices, as suggested by Klenk et al. [40]. The landing surface should also be taken into account for comparison as many studies use a soft landing surface, whereas this study used solid ground. According to Kangas et al., multiple impact peaks were present in real-world falls, and the use of landing surface may affect the results. Often the researchers use a soft landing surface like a mattress to avoid injuries of the subjects, but this approach lowers the impact of the fall [41].

Also, due to the design of the mannequin, the mobile phones were placed at a position on the mannequin torso which could potentially be higher than if worn by elderly people, e.g. if placed in a pocket in their trousers, which means that the free-falling time could be artificially increased during our experiments when compared to actual fall events. A different free-falling time would lead to different acceleration characteristics which could influence the time aspect of the algorithm. In the implemented fall detection algorithm, the maximum time from free-fall detection to impact is one second if a fall is to be detected, but no lower limit is provided in the algorithm. A higher placement likely leads to an increased impact force due to the higher velocity, and thus lower placement could lead to reduced sensitivity. Dai et al. investigated different placements of a smartphone-based accelerometer with a similar algorithm as used in our study; however, the study by Dai et al. also included gyroscope values. The results are inconsistent with these considerations. When the smartphone was placed on the waist in a backward fall, the false-negative percentage was 5.5% while placement on the waist and thigh achieved respectively 2.4% and 2.6% [36]. The differences in the results compared to our study may come from different thresholds and sampling frequencies.Thus, it seems evident that there is a need to calibrate for the height of the user, as well as for placement strategy.

The types of falls are heavily restricted while performing with a mannequin. In this study, the mannequin was set only to fall backwards with a quarter circle rotation. In the study by Dai et al., the results showed a lower accuracy when the mannequin was exposed to lateral and backward falls as compared to forward falls, which indicates that different fall directions should be explored in the future [36].

Also, human-specific falls should be taken into account so that the study can benefit from more deviating falls, which will include behaviour like trying to avoid falling and not lying entirely still. In scenario S1, the subject is supposed to keep lying on the ground. This is relatively simple when using a mannequin, however it is reasonable to believe that human participants will keep moving after a fall, e.g. trying to get up by themselves which could provoke the pedometer to detect false positive steps. If postfall movements are considered steps, the system may simply reject the detected fall motion, and the fall detection will not be transmitted. Our study sought to investigate this particular scenario using a real person, but it does not consider the situations where a real fall has happened and thus does not reflect the different postfall behaviours of people.

As mentioned earlier, the use of a mannequin leads to a higher reproducibility, but it is, however, not the optimal condition, and different results in real-life environments are to be expected. Again, the absence of real-world data is an issue and gives a basis for further evaluation. Kangas et al. collected real-life falls and concluded that the acceleration signals were similar in elderly people's real-life falls and experimental falls performed by middle-aged subjects. However, the authors further conclude that real-life falls provide essential material for further investigation [41]. The conclusion obtained by Kangas et al. did, however, not involve a mannequin but speaks for the fact that experiments can be conducted with people outside the target group.

Scenario S2 used a similar approach but differed from S1 by having the subject take steps after the fall motion detection. This implies a situation where the subject either quickly recovered from the floor or simply did not fall although the fall motion was detected by the fall detection algorithm. Again, the use of a mannequin poses some issues, because it is not capable of walking. The test coordinators tried to hold and walk with the mannequin to avoid interacting with the phones after the fall. To avoid artificial footsteps, the test coordinators could have performed the steps themselves, but that would require taking the phones out of the mannequin's pockets and thereby introduce further bias. People tend to move differently, both in terms of gaits and speeds, and if a person is in the recovery phase after a fall, potential injuries can influence the way of moving [42].

The scenarios S3, S4, and S5 focused on specificity when the subject performed different kinds of ADL. The selected ADL were considered highly relevant for night-time fall incidents, but more ADL with similar characteristics to falls could be added for future work.

In these scenarios, human test subjects were used. It is common to measure sensitivity with young people simulating falls while measuring specificity with elderly people performing ADL [16,24].

Dai et al. evaluated a smartphone approach with human test participants performing ADL, including walking, jogging, standing and sitting. These results achieved a false positive percentage of 8.7–11.2% according to the smartphone placements [36]. This performance is similar to the performance achieved by scenarios S3 to S5. However, walking and jogging were not included in our study as falls detected in these ADL are expected to be discarded by the fall detection algorithm as they include steps, as seen in scenario S2. A potential issue of this reflection is situations where a fall motion is detected while the user is walking, followed by a temporary stationary position of the user. These situations are not further examined but could lead to false positives.

The furniture used in the experiments might have influenced the results in different directions. The chair used in the scenarios S3 and S5 had a height of 47 cm and was cushioned. A smaller chair may lead to a higher impact and thus lower the specificity. The cushioning causes the opposite by attenuating the impact. The same considerations apply to the bed in scenario S4.

7 Conclusion

Our results indicate that the chosen open source algorithm was capable of detecting all falls and thus achieve a sensitivity of 100% when tested on two Android-based smartphones.

We found that the chosen open source algorithm resulted in a substantial number of false positives when only the accelerometer sensor was taken into account, resulting in an unacceptable low specificity, which could lead to false alerts being issued in a real-world setting.

In the S2 scenario where the participants would walk after a detected fall, the added use of a pedometer virtual sensor as part of the algorithm on an Android-based fall detection system resulted in a specificity of 100%. However, this combination of accelerometer and pedometer algorithms still struggles with situations where a fall is detected but not followed by steps to be counted. These scenarios include sitting down on a chair and lying down on a bed, where we only achieved a specificity of 96.25% and 88.5%, respectively.

Thus, more work is needed, including identifying additional scenarios which need to be studied, and how additional sensors and devices may be used to increase the specificity of the fall detection system.

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