F2D: A fall detection system tested with real data from daily life of elderly people

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***Abstract*—Falls among older people remain a very important public healthcare issue. Every year over 11 million falls are registered in the U.S. alone. This paper presents a practical real time fall detection system running on a smartwatch (F2D). A decision module takes into account the rebound after the fall and the residual movement of the user, matching a detected fall pattern to an actual fall. The final decision of a fall event is taken based on the location of the user. To the best of our knowledge, this is the first fall detection system which works on an independent smartwatch, being less stigmatizing for the end user. The fall detection algorithm has been tested by Fondation Suisse pour les Téléthèses (FST), the project partner who is responsible for the commercialization of our system. By analyzing real data of activities of daily life of elderly people, we are confident that F2D meets the demands of a reliable and easily extensible system. This paper highlights the innovative algorithm which takes into account the residual movement and the location of the user to increase the fall detection accuracy. By testing with real data we have a fall detection system ready to be deployed on the market.**

***Keywords*—Fall Detection System, Elderly, Smartwatch, Residual Movement, Accelerometer, Real Data.**

I. INTRODUCTION

Despite extensive preventive efforts, falls continue to be a major source of morbidity and mortality among older adults. Yearly, more than 11 million falls are registered in the U.S. alone [1], leading to a wide spectrum of injuries for this age group. Aside from causing physical injuries, falls can also have dramatic psychological consequences that reduce elderly people's independence [2]. It has been found that after falling, 48% of older people report a fear of falling and 25% report curtailing activities. Moreover, falls can also lead to disability and decreased mobility which often results in increased dependency on others and, hence, an increased need of being admitted to an institution. Finally, one other serious consequence of falling is the "long-lie" condition where a falling person remains on the ground or floor for more than an hour after a fall. The "long-lie" is a sign of weakness, illness and social isolation and is associated with high mortality rates among the elderly. Time spent on the floor can be associated with a fear of falling, muscle damage, pneumonia, pressure sores, dehydration and hypothermia [3], [4].

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In an attempt to minimize these serious consequences of falling, various fall detection systems were developed over the last decade. Also elderly people desire to live at home, so new technologies, such as automated fall detectors, become necessary to support their independence and security. These systems are mainly based on video-cameras [5]–[7], acoustic [8], [9] or inertial sensors [10] and mobile phone technology [11]–[14].

Common fall detection systems are based on a sensor detecting a strong vertical acceleration, launching an alarm when a fall event is recognized. More recent systems usually take into account other sensors able to detect the device's orientation in order to determine whether the user is lying or standing [11], [12].

Even though fall detection has received significant attention in recent years, it still represents a challenging task for two reasons. First, there are several everyday fall-like activities that are hard to distinguish from strong falls. Most of the current approaches define a fall as having greater acceleration than normal daily activities. However, focusing only on a fast acceleration can result in many false alarms during fall-like activities, such as sitting down quickly or lying down on a bed quickly. The second reason is that not all falls are characterized by a fast acceleration of the wrist. The detection of soft falls should be an intrinsic part of creating a successful fall-detection system.

In this paper, we propose a fall detection system (F2D) which works on a smartwatch and therefore it is fixed on the wrist of the person. Using such a device is less stigmatizing for the user. We have avoided the disadvantages of [15] where the solution of the waist-mounted smartphone the authors provide is not feasible for two reasons: 1) Normally people do not wear their phones on the waist but in their pockets. 2) The system will be working only when the smartphone is mounted on the waist and not at other times. Other problems such as the usage of intrusive devices exist in [16] and [17], where the accelerometer and Bluetooth unit are bounded as a wearable unit and placed on the subject's waist or chest.

F2D meets the requirements of reliability, ease of installation and restriction of false positives [18] which are essential for a properly built fall detection system. The evaluation of our fall detection system was performed using partially real data. We used simulated strong and soft falls coming from experts and real non-fall situations that are difficult to distinguish from falls, coming from elderly people's daily life activities. Activities of Daily Living (ADL) are normal activities such as walking, standing, going up and down the stairs.

In F2D we propose an accelerometer-based algorithm considering the residual movement after the fall. This analysis is performed in the decision module of the F2D application which is responsible for the classification of a possible fall pattern being a real fall event or not.

Nowadays, simple smartwatches are very powerful and have a set of sensors that can be used and diverted from their original intent. More computing power and storage on these devices offer greater opportunities. Using a single smartwatch as a device for running the F2D application satisfies the condition of ease of installation of the fall detection system.

An additional component for achieving higher specificity using F2D is the use of the location as contextual data information. A context is defined as any information that can be used to characterize the circumstances in which an event occurs [19]. We use the contextual information in order to refine and strengthen the fall detection system.

The rest of this paper is organized as follows. In Section II our designed fall detection system is described in detail. Experimental results using real data are reported and discussed in Section III. Future improvements of our work to make F2D more robust are presented in Section IV. Finally, a brief conclusion is drawn in Section V.

II. System design

F2D is an Android application running on an AW-420.RX smartwatch of Simvalley Mobile. We have chosen the Android based solution because it is an open source framework designed for mobile devices. The Android SDK provides the API libraries and developer tools necessary to build, test and debug applications for Android. We implemented the prototype in Java using the Android SDK API 22. The fall detection algorithm, which is explained below, is implemented as a background service. When a fall is detected the service informs the main application, which notifies the caretakers (family or friends). There are several notification channels the user can choose from: call, SMS, email or audio message.

A. System overview

We collect data from the accelerometer sensor of the smartwatch which is the most informative sensor regarding the fall detection. We use a threshold based algorithm for the fall detection which takes into account the rebound as well as the residual movement of the user after the fall and the location of the user. The acceleration thresholds were selected based on experiments with different profiles of users. When a critical situation is detected, an alarm is triggered in order to inform the caretakers. The important difference with the traditional systems is that the smartwatch communicates directly with the caretakers with no involvement of a base station and a centralized alarm. Using a smartwatch the user is completely autonomous and the fall detection system is as less invasive as possible.

B. Fall detection algorithm

The user can operate his smartwatch as usual because the fall detection algorithm is implemented in a background service and is running continuously. F2D does not cause any interference with the normal usage of installed applications. The battery consumption is a very important issue that we have to take into account, for making F2D more user-friendly. We decided to use a threshold-based algorithm and not a machine learning approach like [14] as it has less computational complexity and therefore requires the lowest computational power [20]. Adding filters and using contextual information we maximize the sensitivity and the specificity of F2D.

The algorithm distinguishes daily activities from falls. The pattern of a fall must be distinguished from the patterns of these activities. Acceleration data is sampled at 40 Hz from the 3-axis accelerometer sensor embedded in the Android smartwatch. Specifically, the sensor which provides acceleration information without the gravity component (linear acceleration) is used. We calculate the norm of the acceleration for each moment as described in Equation 1.

$$acceleration = \sqrt{x^2 + y^2 + z^2} \tag{1}$$

We have analyzed a set of data with 150 different simulated falls from different people involved in the experiments, from the database of our project partner FST. This company has a long experience in creating and using innovative products adapted to people with disabilities. Thanks to this data we have improved the detection of possible falls. The pattern of a fall is given in three examples which are depicted in Figures 1, 2 and 3 respectively. The time interval between the higher and the lower peak is flexible. More specifically, when a fall takes place, the peak that exceeds the upper threshold of the acceleration corresponds to the hit. After this, the pattern of the fall has a second peak, lower than the first one and exceeding the lower threshold. Finally, the acceleration returns to normal values. This behaviour of the acceleration after the first peak and before the second one represents the rebound after the fall. This rebound, the residual movement right after the fall and the location of the user at that moment, are the three factors that we take into account in the decision for the characterization of a possible fall event as a real fall.

1) Time window: The length of the time window is a crucial part of the algorithm. Based on the set of simulated falls we established that a length of 5 or 6 seconds is sufficient in order to recognize a fall pattern. The main goal of the algorithm is the detection of all falls and at the same time the elimination of false positives. As we can see in Figure 4 we receive the higher values of sensitivity and specificity when the length of the time window is 5 or 6 seconds respectively with an overlap of 1 second for each case. We observe that less than 5 seconds is not enough for the detection of all ADL. Also setting the window to higher values creates a bigger occurrence of false positives.

2) Fall pattern: The next step of the algorithm is the detection of a possible fall. Although in our previous work

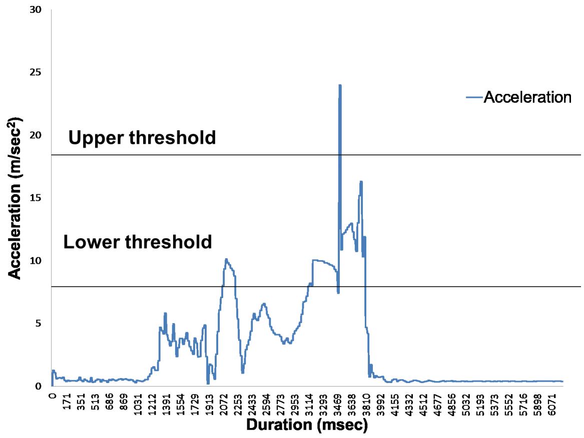

Fig. 1. Example 1.

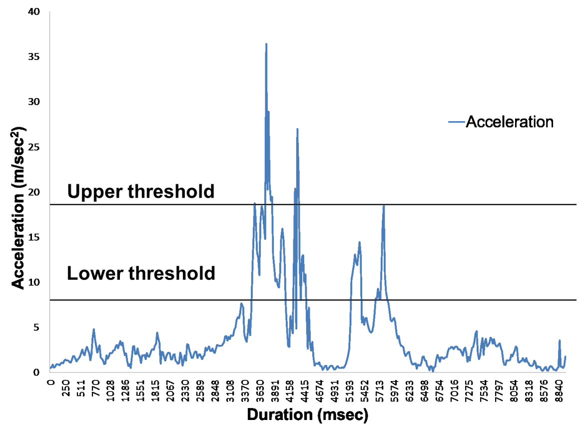

Fig. 2. Example 2.

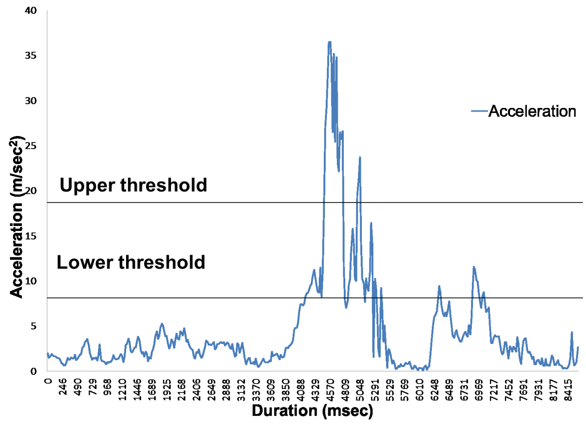

Fig. 3. Example 3.

[21] the acceleration thresholds were fixed, in this work the thresholds are flexible. Analyzing the real ADL from elderly people we were able to find a wide range of acceleration thresholds that keep F2D robust and therefore acceptable for the user. In order to consider an activity as a possible fall the two following conditions must be satisfied: 1) The acceleration

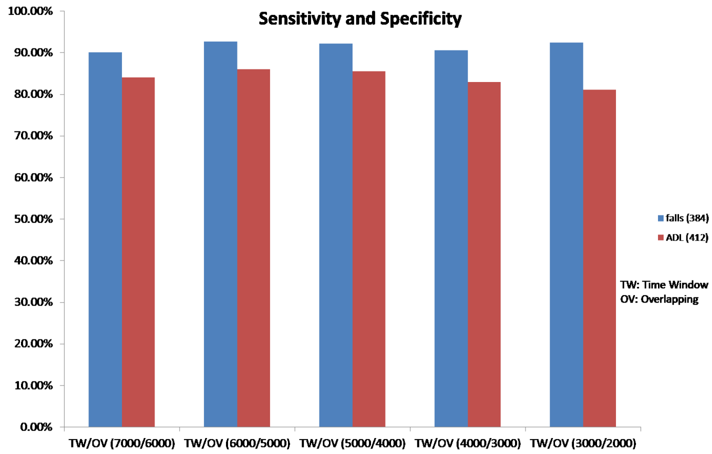

Fig. 4. Time Window.

must exceed an upper threshold which can take values from 10 to 18 m/sec^2 depending on the profile of the user. 2) After a flexible time interval the acceleration must exceed a lower threshold which can take values from 2 to 7 m/sec^2 depending again on the profile of the user. The time difference between the two peaks represents the rebound of the user after a fall. The intensity of this movement depends on the profile of the individual user. The time interval between the higher and the lower peak is flexible but cannot exceed the 0.5 seconds which is the maximum length of the rebound after a fall according to our experiments. Making the time interval flexible instead of giving it fixed values like in our previous work [21] has led to an increase of the specificity of the algorithm of 3%. The ranges of the two thresholds have been selected based on the basic trade-off between detecting all falls and avoiding false positives.

If the two conditions are satisfied during the time window of 6 seconds then a possible fall is suspected. We can see in Figures 1 - 3 that this time window is sufficient for the satisfaction of the two conditions that should happen in order to detect a fall pattern.

3) Decision module: The next step of the fall detection algorithm is the classification of the fall pattern as real. In this decision module a counter increases every time that both conditions of exceeding the thresholds are satisfied. We define X and Y to be the lower and higher acceptable values of the counter respectively. The critical range of the values of the fall counter is $(X \leq counter < Y)$. If $(counter \geq Y)$, then it is due to another activity being performed (e.g., running) which gives the difference in the acceleration values as we can see in Figure 6. Based on the real ADL data that we processed from elderly people we concluded that the value Y that gives the best specificity lays between [5-10] and not 14 comparing to [21]. On the other hand, if $(counter < X)$ where $X = 1$ it means the user at most did a sudden movement with his wrist and so the threshold conditions were not satisfied (e.g., when a user was going down the stairs in Figure 8). The graphical explanation and the structure of the fall detection algorithm are given in Figure 5.

4) After fall activity: One key innovation of F2D is the fact that it takes into account the behaviour of the user after a fall event. Based on the residual movement of the user after the fall we categorize the falls in three types. B1: No movement at all, B2: Small amount of movement after the fall event, B3: Back to normal activity after the fall event. It is clear that, if after a fall the user does not move at all, then the caretakers should immediately be informed and therefore the alarm will be triggered directly. On the other hand, if the user is able to fully recover after a soft fall event, then he is able to cancel the alarm and therefore not disturb the caretakers for no reason. F2D will be released on the market and it requires the least possible false alarms.

5) Location: The last module of F2D is the location module. It includes two different scenarios. The first one is the scenario of the user being outdoors. Then, the fall detection system will work without any further filtering [21], minimizing the probability that we miss any fall that can be dangerous for the end-user.

The second scenario is the case that the end-user is indoors. Then using the exact location of the user in the building (apartment) we can further filter the fall detection events. We use the iBeacon technology for this reason, placing one beacon in each room of the apartment. iBeacon uses Bluetooth low energy proximity sensing to transmit a universally unique identifier picked up by a compatible app or operating system. In our case, the rooms of the building have been pre-marked as dangerous or potentially safe. For instance, the bedroom is a potentially safe room because there is high probability that a possible fall is the movement of the user going to bed. A dangerous room may be the kitchen for example. This approach can be further improved by taking into account, for example the time of day at which the event has occurred. This extra feature will be added to the fall detection system. Then when the fall detection algorithm gives an alarm for a fall we pass this signal to the location module of the fall detection system. If the room is one of the pre-marked as dangerous we consider the event as a fall and we trigger the alarm. Otherwise, in case that the end user is in a place pre-defined as potentially safe room of the apartment (e.g., bedroom) then we give him the opportunity to cancel the alarm that has been triggered because of the detected fall event.

The use of the location as contextual data information leads to an increase of the specificity of the algorithm. Although it is the user that cancels the alarm, it makes the F2D more robust and reduces the probability of losing a fall event and put elderly's lives in danger. On top of this, knowing the precise location where the fall has occurred, it will decrease the reaction time of the caretakers.

C. Emergency actions

If the algorithm decides that a fall has happened and belongs to the B1 or B2 after fall activity then the background service notifies the main application, which in turn triggers an alarm and sends a message to the caretakers. The smartwatch communicates directly with the caretakers. In case of an alarm the loudspeaker of the watch is automatically turned on at a high volume and calls from caretakers are automatically answered. This allows the user to communicate even in uncomfortable positions that could result after a fall.

In case a fall has happened and belongs to the B3 after fall activity, we give the opportunity to the user to cancel the alarm. We do not trigger any alarm since the person fully recovered after the fall event so there is no need to inform the caretakers. We give to the end-user the opportunity to decide if he will use or not the cancel option, since some users may still wish to trigger the alarm even if they have fully recovered after a fall.

There exist two main advantages of using this categorization of the fall types. The first one is the increase of the specificity of the algorithm and so making it more robust. The second one is linked to the first and comes as a result that F2D is going to be available on the market. After making tests with end users from FST and taking into account their feedback we concluded that the possibility of giving the opportunity to the user to cancel the alarm in case of B3 type of fall will make F2D more user friendly.

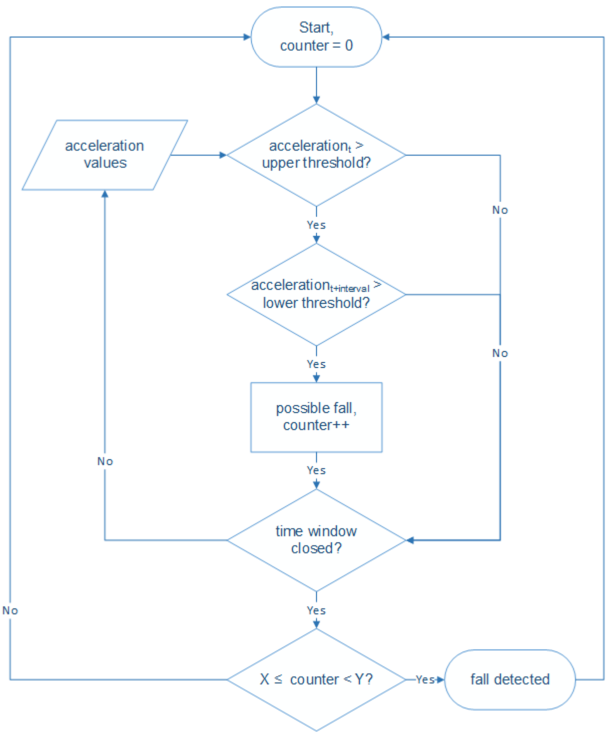

Fig. 5. Fall detection algorithm.

III. Evaluation with Real Data

For the evaluation of the reliability of F2D we performed a series of experiments. We evaluated our fall detection algorithm using a set of simulated falls that we received from our project partner FST. This set consists of 384 simulated falls. We should clarify that these falls have been simulated

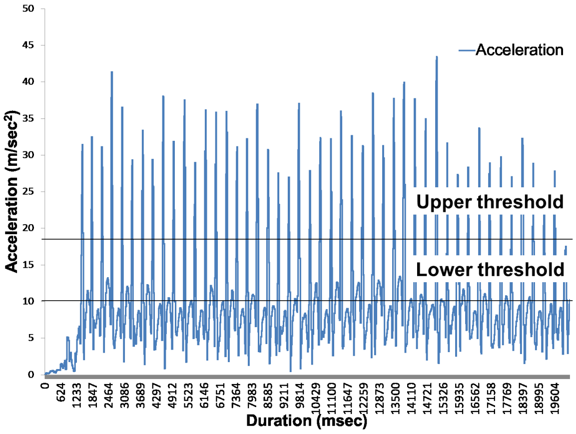

Fig. 6. Running activity.

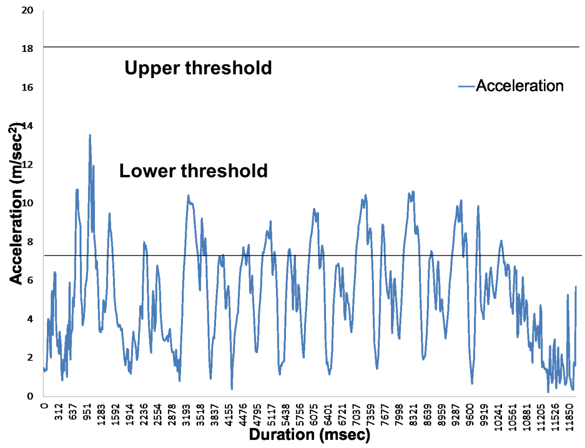

Fig. 7. Walking activity.

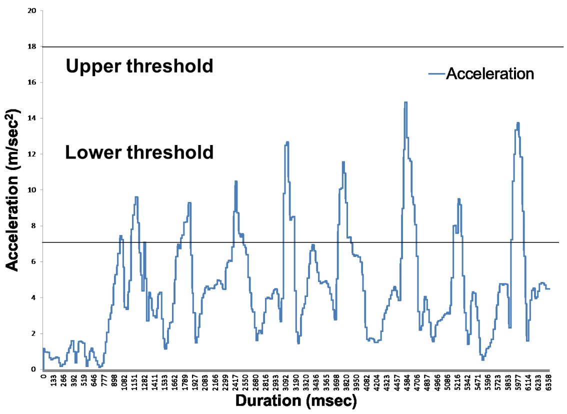

Fig. 8. Going down the stairs.

by experts and therefore they are as similar as possible to real falls from elderly people.

The main innovation is that we evaluated F2D with real ADL from elderly people (412 files) which give us the opportunity to test our system in real life conditions of the target population group. The set of data that we are using is

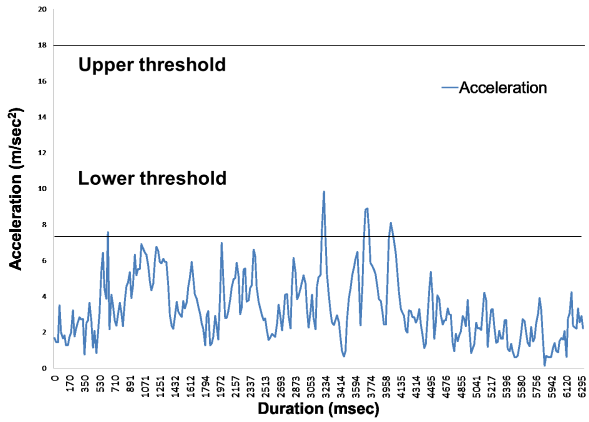

Fig. 9. Going up the stairs.

much larger comparing with other systems [13] where only 34 simulated falls and 200 daily activities simulated by a single young person were used. Our real data has been collected from 6 elderly people with different profiles as reported in Table I.

TABLE I
DIFFERENT PROFILES.

Age	Height (cm)	Weight (kg)
74	158	53
83	165	60
86	160	59
86	175	65
87	156	100
93	155	50

The real ADL were the following: walking, going up the stairs, going down the stairs, standing up from a chair, sitting down on a chair. Based on these facts, it can be noted that the accuracy of our algorithm is quite high. We achieved a true positive rate (sensitivity) of 93.48% for the set of simulated falls and a true negative rate (specificity) of 98.54% for detecting the real ADL from the elderly people. The average of sensitivity and specificity represents the accuracy of the system which is equal to 96.01%. The analytical results are presented in Figure 10.

For the quantitative results analysis, we have created a tool which gives us the opportunity to run the fall detection algorithm against the data that FST has provided. Based on this tool we had the opportunity to systematically test all the improvements made to the algorithm.

Based on the results that we have obtained by testing our fall detection system in real life scenarios, the commercial deployment of F2D is the natural next step. F2D will enlarge the product range the FST is currently providing to their users. Since they work directly with end-users and with end-user organisations, they are able to personalize the system according to the user profile and environment, thus providing a much more accurate and safe system than the generic solutions available in the market. The final application gives the opportunity to the user to select the parameters that correspond to their profile and trade off between fall detection and false alarms as depicted in Figure 11.

More precisely if the user wants to detect a percentage of 99% of the falls, they are able to decrease the thresholds of the final application. This means that they will have some more false alarms and they should sometimes have to cancel the alarm. In the final application these settings will be abstracted to a single "sensitivity" control, which maps discrete sensitivity levels to particular settings of the thresholds and counters.

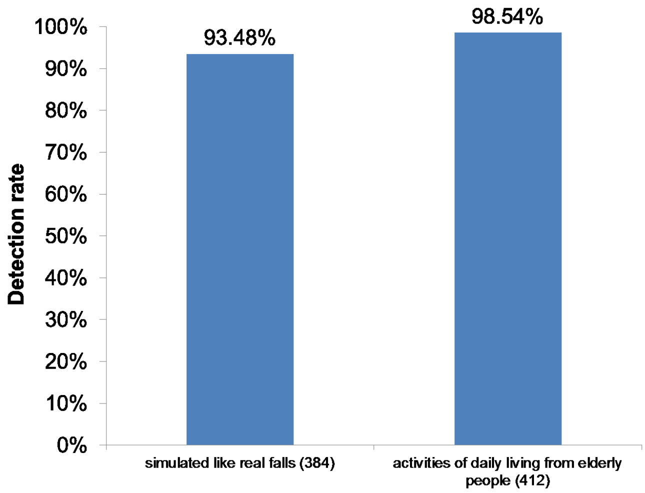

Fig. 10. Accuracy using real data from partner.

Fig. 11. Settings.

We conclude that the F2D system is robust and works reliably. The system is ready to be deployed and it will be soon available for commercial use.

IV. Future work

Our fall detection system (F2D) will be released on the market by the end of the project with our partner FST. The last step for further improvement of the robustness of the system is the reduction of false positives that still exist. We are planning as an extra module to take into account the pulse rate of the user before and after a possible fall event.

V. Conclusions

Fall detection is a research field that has a big impact on the improvement of the daily life of elderly people. In this paper we present the first fall detection system designed to run on an independent smartwatch (F2D). There is no base station (which limits the range), no central alarm station (which is more difficult to manage) and it works on a standard smartwatch. It implies that it is less stigmatizing for the end user, removing the social stigma of wearing a medical device, quite cheap comparing to existing systems and it is easily extendable. F2D uses an innovative fall detection algorithm which takes into account the rebound after the fall, the residual movement and the location of the user in order to match a fall pattern to a real fall.

The main innovation is that we have used real Activities of Daily Living from elderly people, testing our system in real life situations. Also we used data with simulated falls from experts (FST) in reproducing falls simulated like coming from elderly people. These experiments demonstrated that the fall detection system is robust and ready to be released on the market.

Based on the reliability of the fall detection and the restriction of false positives, which are guaranteed by the fall detection algorithm, we have built a system which meets the requirements for deployment and use.

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