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F2D: A location aware 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. In the majority of fall events external support is imperative in order to avoid major consequences. Therefore, the ability to automatically detect these fall events could help reducing the response time and significantly improve the prognosis of fall victims. 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 last module of F2D is the location module which makes our system very useful for nursing homes that host elderly people. 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 testing with real data and achieving an accuracy of 96.01% we have a fall detection system ready to be deployed on the market and by adding the location module we can provide it to nursing homes for elderly people.

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Keywords: Fall Detection System; Elderly; Smartwatch; Residual Movement; Accelerometer; Real Data; Location; Nursing Home

1. 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.

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[3],[4].

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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 reached one more step comparing our work with[5] since our fall detection system works on a smartwatch and it is independent of a central base station. We have avoided the disadvantages of[6] where the solution of the waist-mounted smartphone the authors provide is less feasible for two reasons: 1) Normally people do not keep 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[7] and[8], where the accelerometer and Bluetooth unit are bound as a wearable unit and placed on the subject's waist or chest.

A preliminary version of this work has been reported[9]. For the context awareness of the fall detection system, an indoor positioning algorithm is introduced. This extra algorithm takes into account both the Received Signal Strength Indication (RSSI) of the Bluetooth beacons and the size of the rooms that the beacons are placed in. The context awareness that the location module added to the fall detection system is very important for the final scope of this application. Since we are targeting the care of elderly people who are in a nursing home, knowing the location of the user after a fall is very important. The carer will know in which room the elderly has fallen and therefore they will be able to immediately provide the help that this person needs. Since minimal cost and setup process for the end user were the requirements of the localization system, we used the minimum amount of Bluetooth beacons, that is one Bluetooth beacon per room, and we opted to develop a more sophisticated algorithm for room detection.

The rest of this paper is organized as follows. In Section 2 our fall detection system is described in detail, emphasizing the context awareness that the location approach has provided. Experimental results using real data are reported and discussed in Section 3. Finally, a brief conclusion is drawn in Section 4.

2. System design

F2D is an Android application running on an AW-420.RX smartwatch of Simvalley Mobile. We collect data from the accelerometer sensor of the smartwatch which is the most informative sensor regarding 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 compared 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 non-invasive as possible.

2.1. 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 practical. We decided to use a threshold-based algorithm and not a machine learning approach like[10], as it has less computational complexity and therefore requires the lowest computational power. By 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 as seen in Figure 1 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 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.

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

2.1.1. Fall pattern

The next step of the algorithm is the detection of a possible fall. Although in our previous work[11] the acceleration thresholds were fixed, in this work the thresholds are flexible. By analyzing the real Activities of Daily Living (ADL)

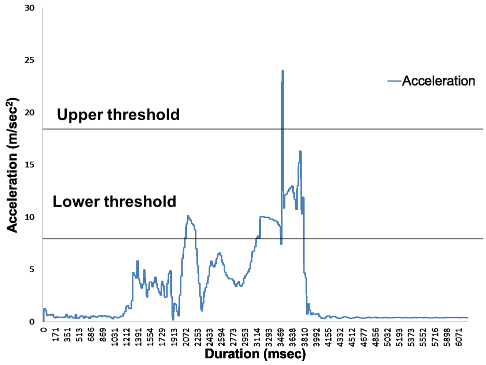

Fig. 1. Example of collected acceleration data during simulated fall.

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: a) The acceleration must exceed an upper threshold which can take values from 10 to 18 m/sec^2 depending on the profile of the user. b) 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 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[11] has led to a 3% increase of the specificity of the algorithm. 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 Figure 1 that this time window is sufficient for the satisfaction of the two conditions in order to detect a fall pattern. 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. Based on the real ADL data that we processed from elderly people, we concluded that the value Y that gives the best specificity lies between the values 5 and 10, and not 14 compared to[11]. 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. The graphical explanation and the structure of the fall detection algorithm are given in Figure 2.

2.1.2. *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 into 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 integrated in a commercial product and as such, it requires the least possible false alarms.

2.2. *Location*

The last module of F2D is the location module. By knowing the precise location where the fall has occurred, it will decrease the reaction time of the caretakers. Therefore the fall detection system can work accurately and provide immediate help to elderly people and caretakers at nursing homes. We use the iBeacon technology for this scenario,

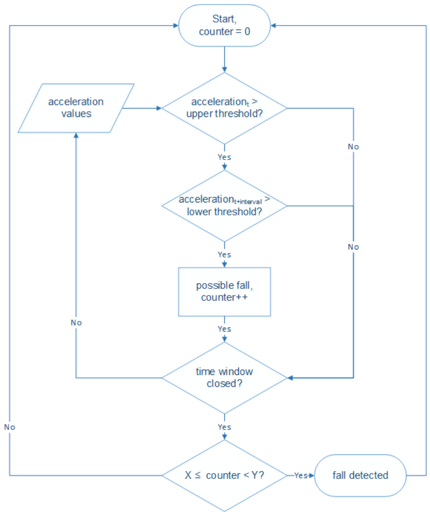

Fig. 2. Fall detection algorithm.

placing one beacon in each room of the apartment. iBeacon uses Bluetooth low energy to transmit a universally unique identifier picked up by a compatible app or operating system.

2.2.1. RSSI and propagation model

In RSSI-based localization, the packets sent from the anchor beacon to the mobile device are used to map the RSSI to a distance by means of a propagation model. The correct calibration of the propagation model is crucial, since the way RSSI is transformed into a distance significantly affects the accuracy of the positioning. The widely known method we use to model the wireless signal propagation loss [12] is given in Equation 2.

$$r = r_0 - 10nlog_{10}(\frac{d}{d_0}) + X_\sigma \tag{2}$$

where d and d_0 denote the real distance and the reference distance respectively, r and r_0 denote the received signal power at the real and at the reference distance respectively, X_σ is a random variable representing the noise in the measured r and n is the path loss exponent, that depends on the transmission channel, the transmitter and the receiver. Using $d_0 = 1$ meter as the reference distance, and assuming X_σ to be a Gaussian distributed random variable with zero mean, the simplified model is used as follows:

$$r = p - 10nlog_{10}(d) \tag{3}$$

where r is the received signal power at the distance d, p is the received signal power of the receiver from a transmitter one meter away and n is again the path loss exponent.

As described in our Bluetooth-based probabilistic room-level localization method [13] based on the surface area of a room and its height we receive an inner and an outer threshold.

2.3. Room dimensions and RSSI thresholds

Let S be the surface area of a room and h be the height of it. Assuming a square room as on Figure 3, the radii of the inner and the outer tangent circles are calculated with Equations 4 and 5 respectively.

$$r_{in} = \frac{\sqrt{S}}{2} \tag{4}$$

$$r_{out} = \sqrt{\frac{S}{2}} \tag{5}$$

Now using the Pythagorean theorem, the hypotenuses are calculated with Equations 6 and 7 respectively.

$$d_{in} = \sqrt{h^2 + \frac{S}{4}} \tag{6}$$

$$d_{out} = \sqrt{h^2 + \frac{S}{2}} \tag{7}$$

Eventually, by substituting the calculated distances of the hypotenuses into the propagation model of Equation 3, the expected RSSI values at those distances are obtained. Defining the inner and the outer RSSI thresholds as the expected RSSI values at the inner and the outer tangent circles of the aforementioned square room respectively, the thresholds are calculated with Equations 8 and 9.

$$threshold_{in} = p - 10nlog_{10}(\sqrt{h^2 + \frac{S}{4}}) \tag{8}$$

$$threshold_{out} = p - 10nlog_{10}(\sqrt{h^2 + \frac{S}{2}}) \tag{9}$$

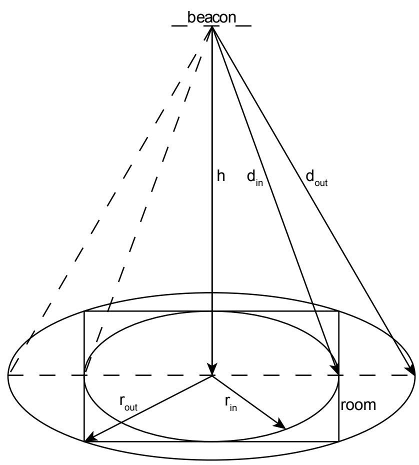

Fig. 3. Square room.

2.3.1. RSSI classification and localization algorithm

For every Bluetooth beacon, the $threshold_{in}$ and $threshold_{out}$ are calculated as described in [13]. Based on their RSSI readings, they fall into one of the following categories. The Strong category (S) when $RSSI > threshold_{in}$, the Medium category (M) when $threshold_{in} > RSSI > threshold_{out}$, the Weak category (W) when $threshold_{out} > RSSI$ and the Not found category (NF) when there is no reading for a specific beacon. The ordering of those categories based on their significance is the following: S > M > W > NF.

For any given moment, for each beacon, a set of its N latest RSSI readings is averaged, so that each beacon can be classified into one of the aforementioned categories. The most significant non empty category is then picked. If only one beacon falls into this category, then the procedure ends and presence is assumed in the room that this specific beacon was placed in. When multiple beacons fall into this category, then a score is calculated for each beacon that is equal to the difference between its measured RSSI and its lower threshold. The lower threshold is equal to $threshold_{in}$ when S is the most significant non empty category, $threshold_{out}$ when M is the most significant non empty category and when W is the most significant non empty category it can be a global minimum of the RSSI readings (e.g. -127) selected by the user. Then the beacon with the highest score wins. In the final case of a draw, the beacon that is placed in the biggest room wins.

3. Performance evaluation

3.1. Fall detection evaluation

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 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 gave 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 much larger comparing with another system [14] 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.

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%. 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 organizations, 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 on 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. 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.

3.2. Indoor localization evaluation

For our experiments we used the Kontakt.io Smart Beacons, set in their default configuration settings (TX Power = 3 and Interval = 350 ms). We gathered RSSI readings at grid locations in each room throughout the floor. At each point, we collected a total of 200 RSSI readings for each beacon, one per second. The receiver was placed on a non-conducting surface at roughly 70 centimetres from the floor. In order to construct the specific propagation model for our application, we placed a Bluetooth beacon in the center of a corridor. Then we took multiple measurements at several points with a known distance from the beacon, ranging from 0.5 to 7 meters. By constructing the line of best fit described by Equation 3, the estimated values of the propagation model parameters were $p = -70.09$ and $n = 1.95$. For our tests we also have empirically set $N = 10$, where N is the size of the set of the latest RSSI readings of each beacon that is averaged. We compare the performance of our indoor positioning system with room-level accuracy with the one without thresholds. That is a system that only considers the magnitude of the RSSI readings and assumes presence in the room with the highest one.

3.2.1. House environment

In this experiment, RSSI readings were collected at 63 different points (9 for every room) as depicted by the circles in Figure 4. The green points are the ones for which the error was improved with the introduction of the localization algorithm, while for the red ones the error deteriorated. Table 1 presents the average error per room and Table 2 presents the specific locations in the house for which the error has changed. For the rest of the points that the error remained unchanged (white points), the average error was 6.07%. As seen in Figure 5, the average error of the points of room A has improved by 8%, of room B by 18.91%, of room E by 13.52%, of room G by 8.9%, while the average accuracy of the points of room D has deteriorated by 9.09%.

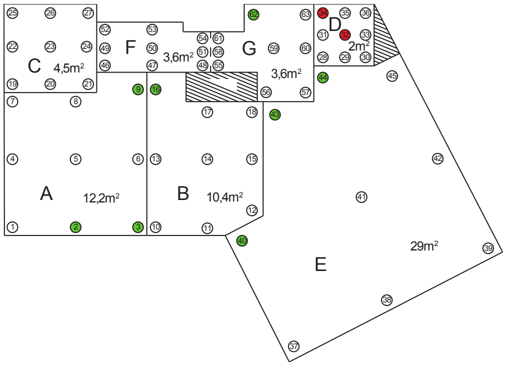

Fig. 4. House evaluation area and targeted locations.

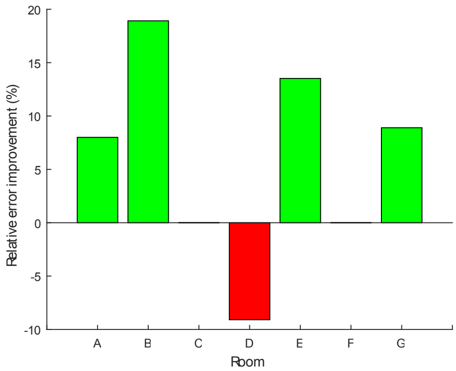

Fig. 5. Improved accuracy in the house evaluation area.

Table 1. Per room error comparison in the house.

Room	Error without the algorithm (%)	Error with the algorithm (%)	Relative error improvement (%)
A	9.72	8.94	+8
B	8.22	6.67	+18.91
C	0	0	0
D	1.83	2	-9.09
E	21.78	18.83	+13.52
F	15.33	15.33	0
G	18.72	17.06	+8.9

4. Conclusion

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 presented 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 an independent smartwatch. It implies that it is less stigmatizing for the end user, removing the social stigma of wearing a medical device. It is 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 and the residual movement in order to match a fall pattern to a real fall. The main innovation is that F2D provides the exact location of the user to a caretaker, this paper presented a threshold-based approach and introduced an algorithm that takes into account both the Received Signal Strength Indication (RSSI) of the Bluetooth beacons and the size of the rooms the beacons are

Table 2. Locations in the house with an error change.

Point	Error without the algorithm (%)	Error with the algorithm (%)	Relative error improvement (%)
2	2.5	2	+20
3	25	24.5	+2
9	29.5	23.5	+20.34
11	9.5	10	-5.26
16	54	39.5	+26.85
32	7.5	8.5	-13.33
34	0.5	1	-100
40	46.5	44.5	+4.3
43	45	24	+46.67
44	100	96.5	+3.5
62	45	30	+33.3

placed in. 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 (provided by FST) in reproducing falls simulated as if they were happening to elderly people. The promising results of these experiments demonstrated that the fall detection system is robust and ready to be released on the market. Moreover being able to locate the user after falling with room-level accuracy makes our fall detection system very useful for nursing homes. 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.

Acknowledgments

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