Personalizable Smartphone Application for Detecting Falls

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***Abstract*—A personalizable fall detector system is presented in this paper. It relies on a semisupervised novelty detection technique and has been implemented in a smartphone application. Thus, it has been tested that the algorithm can run comfortably in this kind of devices. Details about the internal structure of the application and a preliminary evaluation are also shown. The main difference with previous approaches relies in the fact that semisupervised techniques only require activities of daily life for its operation. Departures from normal movements are considered as falls. In this way, no simulated falls are needed, except for testing the performance. Therefore, the system can be easily adapted to each user.**

I. INTRODUCTION

Unintentional falls are a common occurrence among older adults. According to the World Health Organization [1] about more than 30% of people aged 65 and over fall every year. Thus, this has already become a public health problem that will increase within ageing societies. A quick intervention after a fall is essential to diminish its adverse effects [2]. Therefore, finding a robust fall detector is a very relevant research goal.

There are several sensors that can be used to detect falls [3]: cameras, infrared, pressure or floor sensors, accelerometers, etc. There is no perfect technique or sensor and each one has its advantages. Accelerometers are very popular since they provide a direct way to measure body's movements and they have been used for a long time in this field. More recently, many authors have proposed to use smartphones for fall detection [4-9], since they have built-in accelerometers. The acceleration readings during falls show typical peaks and valleys. Therefore threshold techniques have been used to detect falls [10,11]. Other authors have used more sophisticated Machine Learning techniques [5,12,13] to discriminate between falls and activities of daily living (ADL) in order to reduce the number of false alarms. However, this number is still a concern and the performance decreases when facing real world falls as shown by Bagala et al. [14].

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In this paper we present a smartphone application that distinguishes from previous ones in several aspects. Firstly, it is based on a semisupervised anomaly (or novelty) detection technique (we adopt the classification of Chandola et al.[15]). Acceleration patterns are compared with ADL using a nearest neighbor rule and, if this difference is very high, a fall is detected. Secondly, as a consequence of using a semisupervised approach, the detector can be personalized and updated very easily. For that purpose, when a new user wears it, new ADL records can be stored and the system can be retrained on the fly. In this way, the detector adapts itself to each person, new movements or new ways of carrying the phone, leading to an increase in performance with respect to a generic system. Thirdly, the application integrates into an integral assistive system composed of a web server and a smartphone application that provides geolocalization, press-for-help button, geofence and personalized reminders [16]. In this paper, we focus on the fall detection module.

The rest of the paper is organized as follows. In section II we present the data set used for off-line analysis, the algorithms and how the novelty detection method is implemented in smartphones. In section III we present the results and a brief discussion. In section IV, we draw some conclusions and indicate lines of future work.

II. MATERIALS AND METHODS

A. Data set

In a previous research we collected a data set that we have used for off-line analysis [17]. It includes about 8000 ADL and 500 falls from 10 volunteers. The volunteer were 7 males and 3 females, ranging from 20 to 42 years old (31.3 ± 8.1 years), body mass 54 to 98 kg (69.2±13.1 kg) and height from 1.61 to 1.84 m (1.73±0.08 m). Eight types of falls were simulated: forward and backward falls, left and right lateral falls, syncope, sitting on empty chair, falls with an obstacle and falls with compensation strategies. Each ADL or fall contains information about the acceleration in a 6 s window time around an acceleration peak sampled at 50 Hz. The central 1 s was used as the main input feature vector for the algorithms since falls have been reported to be very short [18], while the last second was used to test a condition of lack of movement, that is a period of time in which the person is supposed to rest after a fall.

B. Algorithms and their evaluation

The novelty detection algorithm was based on a nearest neighbor rule (NN). The algorithm works as follows. A training set of ADL vectors must be available, $\mathbf{x}_i$ i=1...N. Then, given a new input vector, $\mathbf{y}$, the minimum distance is

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obtained as $d_{NN}=\min_i(d(\mathbf{x}_i,\mathbf{y}))$. If this distance is higher than a threshold, $d> \theta_d$, the new input is considered anomalous and a fall alarm is triggered. By varying the threshold θ_d, the receiver-operator characteristic (ROC) curve can be plotted using a test data set.

This method does not require any complex training and can be easily customized. Thus it is very suitable for a customizable smartphone application.

For comparison purposes, we have also implemented a threshold-based algorithm. This kind of algorithms is very popular for smartphones since it has very low computation time. A fall is detected when, in a given time window, the difference between the peak and the valley in the acceleration shape exceeds a threshold, θ_a. By varying the threshold θ_a the ROC curve can be obtained, as in the case of NN.

In both algorithms, a fall is detected only if the additional condition of lack of movement is also fulfilled. This has been shown to remove many false positives [18].

The comparison between NN and the threshold-based algorithm was performed by doing a ten-fold cross validation. We have selected the area under the ROC (AUC) as the figure of merit of the detector. Then we also studied the effect of personalization in NN. For that purpose we compared a generic and a personalized detector in the following way. For a given person, both algorithms were tested using a validation data set from his or her falls and ADL. However, the exemplar data sets used by NN were different depending on the version. In the generic version, data come from the remaining volunteers, while the personalized version used the rest of the data from that person. In this way we simulated the situation in which the system can be updated with new ADL when a different user is carrying the device and, after some time, all the stored ADL are a register of his or her own typical movements. For each person, this was repeated ten times for cross-validation.

C. Structure of the smartphone application

The application was developed for Android devices. The main user interface (Android Activity) is just one press-for-help button common to all the modules of the integrated assistive system. The core of fall detection itself is implemented in a background program (Android Service) (fig. 1) that loads initial ADL and starts the accelerometer. Acceleration values are stored in a vector. The application mimics the way in which the ADL data set for off-line analysis was obtained. Each time a new acceleration value is available, the application checks for peak values in the vector (at least 1.5g, g=gravity acceleration) and lack of movement some time after the peak. If both conditions are met, the time around the peak is extracted to feed the classifier. To avoid diminishing application responsiveness, the classifier algorithm run as a parallel task, which was implemented using the Async Task class in Android. If the novelty nearest neighbor detection algorithm reports a fall, an alert sound is played and a new interface (Android Activity) appears on the screen. The voice and the screen ask the user whether he or she needs help (fig. 2a). By pressing the "No" button, the alarm is cancelled as it is considered a false alarm. Otherwise (if the "Yes" option is selected or no button is pressed after a 15 second time period), a call is made to the caregiver's phone. The app also sends an alert to the web page server (fig. 2b). The number of potential falls is shown in the web page, so the caregiver can see and acknowledge the falls of the people he/she is charge of. The phone number to call in case of emergency can be configured through the web page.

If the detector reports an ADL instead, the new ADL substitutes an old one. In this way, the system adapts itself to new users or behaviors, like carrying the phone in a different place. For the experiments shown in this paper, the application had a set of 400 predefined ADL in the exemplar data set. This number was fixed and the predefined records were substituted by user's records as they were acquired.

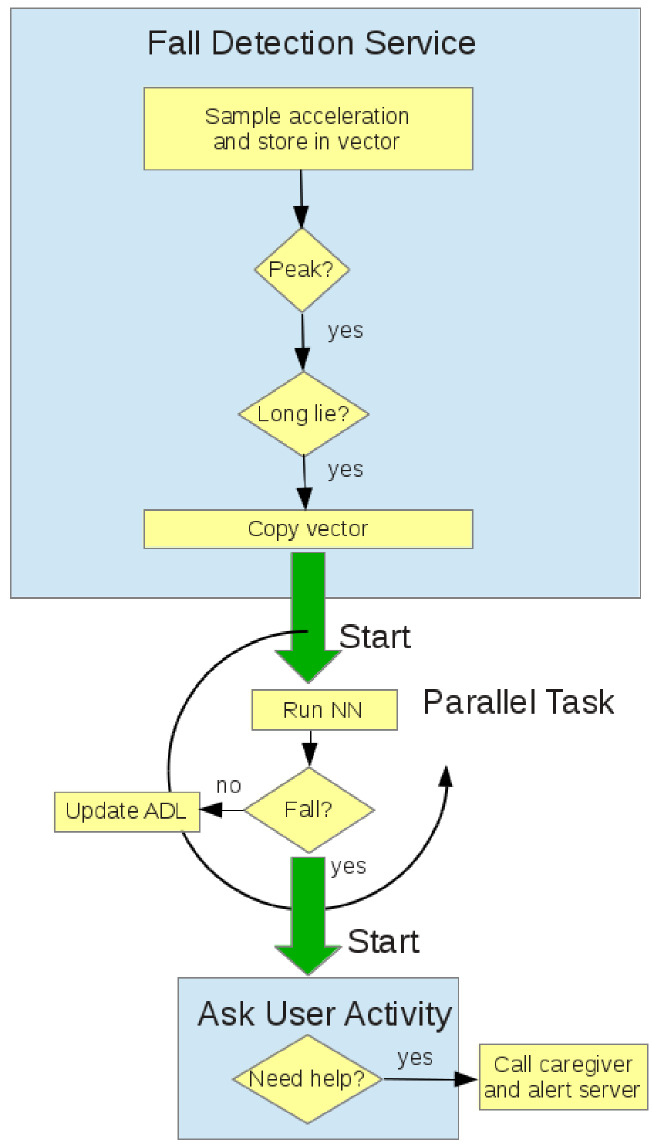

Figure 1. Schema of the Android application for fall detection.

a)

b)

Figure 2. Screenshots of the application: a) Web server; b) Smartphone after a potential fall has been detected.

III. RESULTS AND DISCUSSION

Two different types of test have been conducted:

- On the one hand, an off-line analysis using the data collected as explained in section II.
- On the other hand, a real world experiment involving several volunteers who carried the smartphone application during several days.

A. *Off-line analysis*

The results of the comparison of the two algorithms are shown in table I. NN has a far better performance than a threshold-based algorithm, even if it is based only on ADL. This is also graphically shown in fig. 3, where the difference between the ROC curves can be appreciated.

The results of the personalization study are shown in table II. For 9 out of 10 people, the personalization is better than the generic algorithm. However in some cases the difference is very small, so we applied a t-test taking the null hypothesis that AUC is the same in both cases. For seven people the hypothesis could be clearly rejected (p-value < 0.01), while it could not for the remaining. Thus, it seems that the personalization is a valuable option for many people, while for others the performance is similar to that of a generic detector.

B. *Test under real-life conditions*

Besides the off-line analysis, four people also carried the smartphone for two periods of several days (between three or four days each one). Their characteristics are found in table III. First, a version without updating was used in the phone. Then, we installed the final application in which new ADL are recorded and substitute the predefined ones. In this way we could compare the effect of personalization in real-life. For the comparison, we used some statistics concerning the square of the nearest neighbor distance, d^2_{NN} for all the ADL that took place during the testing period. We also set a threshold to have a theoretical FPR value of 5% determined in an off-line analysis. In our experiments, the 400 ADL predefined data set was completely updated in about 2 or 3 days.

TABLE I. PERFORMANCE COMPARISON: AUC MEAN (STD)

NN	Threshold-based	Difference
0.977 (0.010)	0.939 (0.011)	0.038 (0.007)

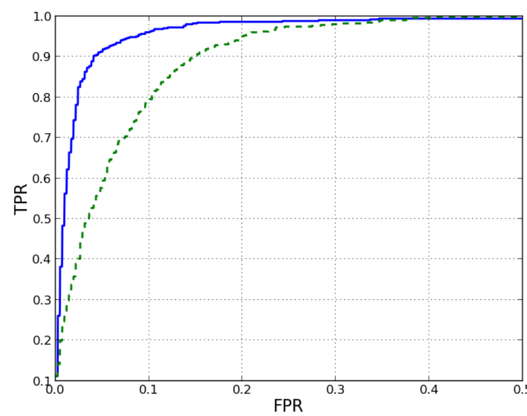

Figure 3. Comparison of ROC curves for NN (blue, solid line) and the threshold-based algorithm (green, dashed line).

TABLE II. EFFECT OF PERSONALIZATION: AUC MEAN (STD)

Person	Custom	Generic	Difference	p-value
0	0.968(0.010)	0.963(0.012)	0.005(0.004)	<0.01
1	0.995(0.004)	0.994(0.006)	0.001(0.004)	0.58
2	0.958(0.014)	0.958(0.011)	0.000(0.005)	0.75
3	0.980(0.012)	0.966(0.013)	0.014(0.004)	<0.01
4	0.978(0.009)	0.976(0.008)	0.002(0.005)	0.16
5	0.977(0.032)	0.943(0.028)	0.034(0.026)	<0.01
6	0.971(0.012)	0.950(0.013)	0.021(0.006)	<0.01
7	0.974(0.011)	0.968(0.011)	0.006(0.005)	<0.01
8	0.984(0.019)	0.982(0.018)	0.002(0.002)	<0.01
9	0.992(0.008)	0.988(0.009)	0.004(0.003)	<0.01
Average	0.978	0.969	0.009	

The results of the comparison are shown in table IV. For the four people the average value of d^2_{NN} decreases when the updating is switched on, as a result of the personalization. This is reflected in the number of false alarms per day that decreases as well. However, the difference is highly dependent on the subject. For person 2 it is rather low, while for the remaining people dramatic. The number of false alarms is in keeping with those obtained in [14].

TABLE III. CHARACTERISTICS OF PEOPLE (H=HEIGHT, W=WEIGHT)

Person	Sex	Age	H (cm)	W (kg)	Phone
0	M	28	178	72	Samsung Galaxy S II
1	M	27	176	65	HTC Wild Fire S
2	M	42	178	57	Samsung Galaxy Mini
3	F	42	161	47	Samsun Galaxy S4

TABLE IV. EFFECT OF UPDATING ADL IN SOME PEOPLE CARRYING THE PHONE

Person		d^2_{NN} mean (std)	d^2_{NN} median	FP / day
0	No updating	120 (101)	88	3.1
	Updating	88 (69)	69	0.7
1	No updating	223 (211)	140	13.5
	Updating	112 (99)	76	2.8
2	No updating	101 (106)	67	3.9
	Updating	91 (91)	62	3.4
3	No updating	148 (148)	102	5.1
	Updating	144 (115)	110	1.4

IV. CONCLUSIONS AND FUTURE WORK

We have successfully implemented a smartphone application for fall detection that adapts itself to new users and situations. It has a better performance than a threshold-based algorithm and is simple enough to be run comfortably in any smartphone. The preliminary evaluation of the system shows that personalization is a valuable option to decrease the number of false alarms. Further research is needed to study the effect of personalization among different class of people. However, the number of alarms is still high. Fall detection is a complex problem and there are many aspects involved that can change performance under real-life conditions: the way to extract acceleration samples from the continuous flow of movements, the features used, the algorithm to classify, the post-fall phase treatment and many more. We plan to test more complex algorithms, both supervised and semisupervised, and include information from orientation to feed the classifier. We believe that personalization is an important research topic since the target audience of fall detector, the elderly, might have different characteristics from those of the people involved in experiments, usually young or middle-age volunteers [19, 20].

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