Recognizing Human Activities and Detecting Falls in Real-time

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Abstract. The paper presents a system that recognizes human activities and detects falls in real-time. It consists of two wearable accelerometers placed on the user's torso and thigh. The system is tuned for robustness and real-time performance by combining domain-specific rules and classifiers trained with machine learning. The offline evaluation of the system's performance was conducted on a dataset containing a wide range of activities and different types of falls. The F-measure of the activity recognition and fall detection were 96% and 78%, respectively. Additionally, the system was evaluated at the EvAAL-2013 activity recognition competition and awarded the first place, achieving the score of 83.6%, which was for 14.2 percentage points better than the second-place system. The competition's evaluation was performed in a living lab using several criteria: recognition performance, user-acceptance, recognition delay, system installation complexity and interoperability with other systems.

Keywords: Activity recognition; Fall detection; Ambient assisted living; Machine learning; Rules; Accelerometers.

1 Introduction

The world's population is aging rapidly, threatening to overwhelm the society's capacity to take care of its elderly members. The percentage of persons aged 65 or over in developed countries is projected to rise from 7.5% in 2009 to 16% in 2050 [1]. This is driving the development of innovative ambient assisted living (AAL) technologies to help the elderly live independently for longer and with minimal support from the working-age population [2][3]. To provide timely and appropriate assistance, AAL systems must understand the user's situation and context, making activity recognition (AR) an essential component [4][5][6]. Fall detection (FD) is an important component of many AAL systems because approximately half of the hospitalizations of the elderly are caused by falls [7]. Fear of falling is an important cause for nursing home admission [8], and "the long lie" (not being able to get up and call for help) is an important predictor of death within six months [9].

This paper presents the RAReFall system, which recognizes the user's activities and detects falls in real time. The architecture of the system combines rules to recognize postures (static activities), which ensure the behavior of the system is predictable and robust, and classifiers trained with machine learning (ML) algorithms, to recognize dynamic activities, for which the rules are not sufficiently accurate. For the FD, rules are used that take into account high accelerations associated with falls and the recognized horizontal orientation (e.g., falling is often followed by lying).

Initially, the RAReFall system was evaluated offline, on a dataset containing a wide range of activities and different types of falls. Its recognition performance was very high, encouraging us to take part in the EvAAL-2013 activity recognition competition [10], which evaluates AR systems in a living lab. The RAReFall system was evaluated best on a combination of criteria: recognition performance, user-acceptance, recognition delay, system installation complexity and interoperability with other systems.

2 Related Work

AR approaches can be divided into those using non-wearable sensors and those using the wearable type. The most common non-wearable approach is based on cameras [11]. Although this approach is physically less intrusive for the user compared to the wearable sensors, it suffers from problems such as low image resolution, target occlusion, time-consuming processing, and often the biggest issue is user privacy: the user has to accept the fact that a camera will record him/her. The most exploited and probably the most mature approach to AR is using wearable accelerometers, which are both inexpensive and effective [12][13]. This is also the reason why wearable accelerometers were used for our RAReFall system.

There are two common types of wearable-sensor approaches to AR that have proved to be successful: using domain knowledge encoded with rules, and using ML. The first approach uses rules applied to accelerometer's data in order to recognize an activity. This approach proved to be successful for static activities such as: standing, sitting and lying [12]. The second approach is based on known classification methods, e.g., decision trees, Random Forest, SVM, kNN, Naive Bayes, etc., which are applied on the accelerometer's data [13]. The problem with this approach is that the training data should include each activity of the user performed in all possible ways, e.g., lying backwards, lying sideway, lying on the back, etc. This makes the ML approach unpredictable and less-attractive for real-life usage. In our approach we overcome this issue by combining the two approaches, thus we use domain rules for some of the static activities and ML for the others. This way, we increase the understandability of the system and also making it more predictable and robust for situations that are not included in the training data.

3 System Implementation

The RAReFall system is shown in Fig. 1. It consists of two accelerometers, placed on the user's torso and the thigh. The accelerometers can be attached to the user's body in several ways, making the system more user-acceptable and also adjustable to the occasion (e.g., worn indoors or outdoors). Some examples of how and where the sensors can be worn include, but are not limited to:

- torso: worn on a cord around neck, elastic strap, pockets sewn into garment
- thigh: in the pocket, elastic strap, pocket sewn into garment

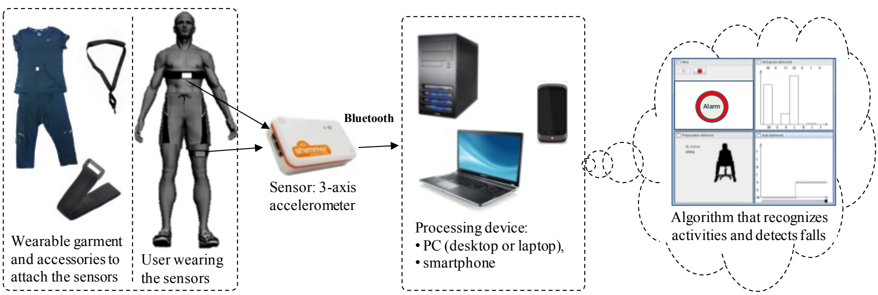

Figure 1. RAReFall system overview.

The placement of the sensors was chosen as a trade-off between the physical intrusiveness and the performance in preliminary tests [14][15]. The Shimmer accelerometer-sensor platform [16] was chosen because it has a reasonable battery life, compact size, 3-axis accelerometer and uses Bluetooth communication. In general, any sensor with 3-axis accelerometer and Bluetooth module can be used.

The sensors' data are received and processed on a Bluetooth-enabled processing device which processes the data in real time. The current implementation of the system is developed for indoor usage (a house, a flat, etc.); therefore a laptop/desktop PC is used for processing. Additionally, the PC is equipped with a long-range Bluetooth antenna in order to ensure the maximum reliability and signal strength (theoretically covering up to 300 meters radius, which is more than enough for indoors coverage). However a smartphone implementation is technologically possible and considered for future work.

4 Methods

The AR and FD pipeline is shown in Fig. 2. First, the sensors transmit the raw acceleration data over Bluetooth to the processing unit, i.e., PC. The data from both sensors are then preprocessed: synchronized, filtered and segmented. Then the pipeline splits in two. On one side, the segmented data are transformed into feature vectors for the AR module, which recognizes the user's activity. On the other side, the FD module checks the acceleration for falls. If a fall pattern is recognized, the user's orientation is checked. If the orientation corresponds to lying, a fall is detected. Both the AR and FD modules are evaluating the user's situation every 250 milliseconds using the last 2 seconds of sensor data. For instance, if the current system time is denoted with t, the FD module evaluates fall events in the [t – 2 s, t – 1 s] interval, and the [t – 1 s, t] interval is used to check if the user's orientation corresponds to lying. If the fall event is detected and the orientation is correct, the reported activity is falling, otherwise the reported activity is computed with the AR module in the [t – 2 s, t] interval. The system thus reports the user's activity and detects falls with a two-second delay. In the following sections, the AR and FD methods are briefly described. More technical details can be found in our previous work, [17] for AR, and [18] for FD.

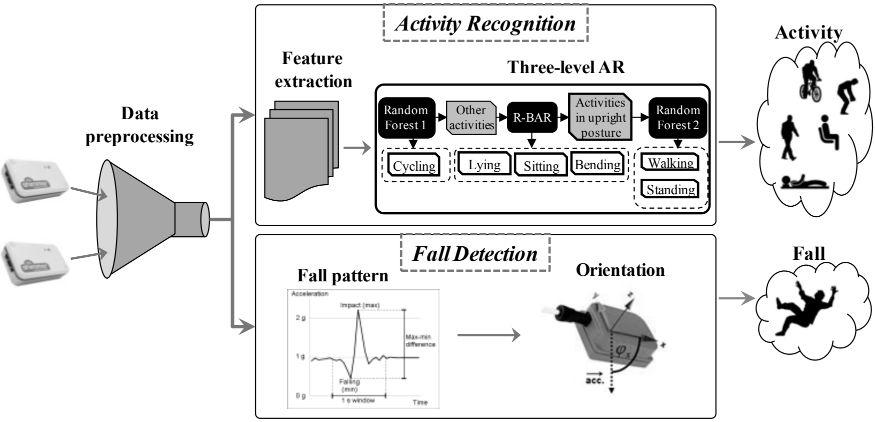

Figure 2. The data and recognition flow in the RAReFall system.

4.1 Activity Recognition

In the AR module, the activities are recognized by a three-level scheme [17]. The AR scheme was developed after empirical analysis of the data, which showed that some activities (such as cycling) are better recognized by a classifier trained only to distinguish that particular activity from the others. Therefore, on the first level the feature vector is fed into a Random Forest classifier, which is trained to distinguish cycling from the other activities. If the activity is not classified as cycling, the feature vector is passed to the second level, where the activities are recognized by rules. On this level, only the features that the best represent the sensor orientation are used (using component of the acceleration that corresponds to the gravity). The following activities are recognized at this level: sitting, lying, bending, and upright posture. If the recognized activity is the upright posture, the third level of AR is used to distinguish between standing and walking. The feature vector is again fed into a Random Forest classifier, which is trained to separate these two activities.

4.2 Fall Detection

A typical acceleration pattern during a fall, measured by an accelerometer placed on the abdomen, is a decrease in acceleration followed by an increase [18]. This is because an accelerometer, when stationary, registers 1 g (the Earth's gravity) and during free fall 0 g. When a person starts falling, the acceleration decreases from 1 g to around 0.5 g (perfect free fall is never achieved). Upon the impact with the ground, a short strong increase in the acceleration is measured.

To detect acceleration fall patterns, we used the length of the acceleration vector to ignore the direction of the acceleration. The minimum and the maximum acceleration within a one-second window were measured. If the difference between them exceeded 1 g and the maximum came after the minimum, a fall pattern was found. We augmented the fall-pattern detection with the measurement of the user's orientation after a potential fall. We assumed that the orientation of the user's body after a fall cannot be upright. Therefore, a fall was detected if a fall pattern was detected and the orientation in the next second was not upright.

5 Evaluation

5.1 Offline Evaluation

The offline evaluation of the RAReFall system was performed in order to check the recognition performance of the methods, using a pre-recorded dataset (publicly available at: http://dis.ijs.si/ami-repository/). A 90-minute, test scenario was designed in cooperation with a medical expert to capture the real-life conditions of a person's behavior, although it was recorded in a laboratory. The scenario was performed by 10 volunteers. It included the following elementary activities: standing, sitting, lying, on all fours, bending (standing leaning), walking and cycling. These activities were selected as they are the most common elementary, everyday-life activities.

Table 1 shows the offline performance of the RAReFall system on the pre-recorded dataset. The performance of the AR is high, achieving 96.36% F-measure score averaged over all activities. The performance of the FD shows that 93.3% of the falls were detected (recall value), and 66.7% of all the fall detections were actually falls (precision value), giving the final F-measure of 77.8%. The detailed FD results (Table 2) show that the first event – tripping (quick uncontrolled fall) was detected each time (15 out of all 15 events). The next event, fainting, was detected 13 out of 15 times. The next two events were the non-fall events that are difficult to distinguish from the fast falls because of the high acceleration. Because the FD module also checks the user's orientation after a potential fall, it was able to distinguish quickly sitting on the chair from the falls, since the user ended up in the upright posture. However, this was not the case for quickly lying in the bed (13 false detections). For correct recognition of this event, additional information about the user would be needed, e.g., user's location.

Table 1. RAReFall system - offline performance.

Performance	Activity Recognition	Fall Detection
Recall	96.19%	93.33%
Precision	96.53%	66.67%
F-measure	96.36%	77.78%

Table 2. RAReFall system - Fall detection detailed results.

Events	Detected/All
Tripping	15/15
Fainting	13/15
Quickly lying	13/15
Quickly sitting	1/15
Other	0

5.2 Online Evaluation - EvAAL Competition

The initial results were promising, but they were performed offline, on pre-recorded dataset and not in real-life situation. Therefore, we decided to participate in the EvAAL-2013 activity recognition competition [10], which evaluates AR systems intended to be used by the elderly using the following criteria:

- Recognition performance − how accurately the system recognizes the activities.
- Recognition delay – elapsed time between the time at which the user begins an activity and the time at which the system recognizes it.
- User acceptance − how invasive the AR system is in the user’s daily life; this and the following two parameters were evaluated by an evaluation committee.
- Installation complexity – how much effort is required to install the AR system in the living lab.
- Interoperability with AAL systems – the metrics used are: the use of open-source solutions, availability of libraries for development, integration with standards.

EvAAL-AR is a live competition taking place in a living lab, where the competitors install and run their systems, recognizing the activities of an actor. An evaluation committee oversees the competition and evaluates the systems using the aforementioned set of usability criteria. The '12 and '13 competitions were held in the CIAmI Living Lab in Valencia, Spain.

Table 3 shows the scores on the scale of 0–10 for the five criteria (accuracy, delay, installation time, user acceptance and interoperability) for the '12 and '13 editions. Due to the change in the weights of the criteria for the ’13 edition, the final scores for the both years' rules are included. Our RAReFall system was evaluated as best, achieving the score of 83.6%, which was for 14.2 percentage points better than the second-place system (CNR-Italy). Moreover, our system obtained the highest final score for the both years, by achieving not only high accuracy, but also scoring very well on the other criteria.

Table 3. EvAAL-AR '12 and '13 teams and results (score: from 0 to 10).

	Team	Accuracy	Delay	Installation complexity	User Acceptance	Interoper-ability	Overall score '12	Overall score '13
EvAAL-AR '13	**RAReFall (Slovenia)**	**6.94**	**10**	**10**	**8.55**	**7.2**	**8.45**	**8.36**
	CNR (Italy)	4.04	10	10	7.04	6.15	7.19	6.94
	Seville'13 (Spain)	4.68	9	10	6.99	5.54	7.05	6.89
	Chiba'13 (Japan)	4.43	10	0	5.44	2.24	4.8	4.86
EvAAL-AR '12	Seville'12 (Spain)	4.33	9	10	7.47	7.63	7.39	7.07
	CMU&Utah (USA)	7.17	9	0	7.93	6.15	6.5	6.51
	Chiba'12 (Japan)	1.44	5	0	5.6	5.09	3.52	3.13
	Dublin (Ireland)	0	0	10	5.2	1.25	2.99	2.67

6 Discussion

This paper presented a system for real-time AR and FD, called RAReFall. It was designed for robust performance in real life, so it uses a combination of relatively mature but finely tuned methods. Similar implementations of our system are widely used in the observational studies (evaluated by hundreds of people) of two European projects: Confidence and Chiron. In the first one, the AR module is used to detect falls and daily behavior change of elderly. In the second the AR is used in order to estimate the energy expenditure of users which have heart-related problems.

The competition setting is closer to real life than most AR evaluations, so our result at the competition is evidence of RAReFall's practical applicability. Current implementation of the system is intended to be used indoors; however a smartphone implementation is considered for future development, which will make the system usable for outdoors as well. We are also working on a system that will have only one wearable device comprising several sensors (accelerometer, ECG, body temperature, body humidity, etc.). Using these sensors' data, the system should not only recognize the activity of the user, but also should reason about the user's behavior and health in general.

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For wider interest

The world's population is aging rapidly, threatening to overwhelm the society's capacity to take care of its elderly members. This is driving the development of innovative ambient assisted living (AAL) technologies to help the elderly live independently for longer and with minimal support from the working-age population. To provide timely and appropriate assistance, AAL systems must understand the user's situation and context, making activity recognition (AR) task an essential component. Detection of falls is also another important component of many AAL systems because approximately half of the hospitalizations of the elderly are caused by falls.

This paper presents the RAReFall (**R**eal-time **A**ctivity **Re**cognition and **Fall** detection) system, which recognizes the user's activities and detects falls in real time. The RAReFall system consists of two wearable sensors (accelerometers), placed on the user's torso and the thigh, and a laptop that receives the data through Bluetooth and analyzes the data in real-time using artificial intelligence algorithms. The algorithm architecture combines domain-expert rules to recognize postures (static activities), which ensure the behavior of the system is predictable and robust, and classifiers trained with machine learning algorithms, to recognize dynamic activities, for which the rules are not sufficiently accurate. For the fall detection, rules are used that take into account high accelerations associated with falls and the recognized horizontal orientation (e.g., falling is often followed by lying).

Initially, the RAReFall system was evaluated offline, on a dataset containing a wide range of activities and different types of falls. The accuracy of the activity recognition and fall detection were 96% and 93%, respectively, encouraging us to take part in the international EvAAL-2013 activity recognition competition, which evaluates AR systems in a living lab. The RAReFall system was awarded the first place, achieving the score of 83.6% (over all criteria), which was for 14.2 percentage points better than the second-place system. The evaluation was performed in a living lab using several criteria: recognition performance, user-acceptance, recognition delay, system installation complexity and interoperability with other systems.