RAReFall - Real-time Activity Recognition and Fall Detection System

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***Abstract*— This demo paper presents the RAReFall system, which is a real-time activity recognition and fall detection system. It is tuned for robustness and real-time performance by combining human-understandable rules and classifiers trained with machine learning algorithms. The system consists of two wearable accelerometers sewn into elastic sports-wear, placed on the abdomen and the right thigh. The recognition of the user's activities and detection of falls is performed on a laptop using the raw sensors' data acquired through Bluetooth. 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 99% 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 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

I. 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 a good predictor of death within six months [9].

This demo 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.

II. SYSTEM IMPLEMENTATION

The RAReFall system (shown in Fig. 1.) consists of two accelerometers sewn into elastic sports-wear, placed on the abdomen and the right thigh. The AR and FD are performed on a laptop using the raw sensors data acquired through Bluetooth.

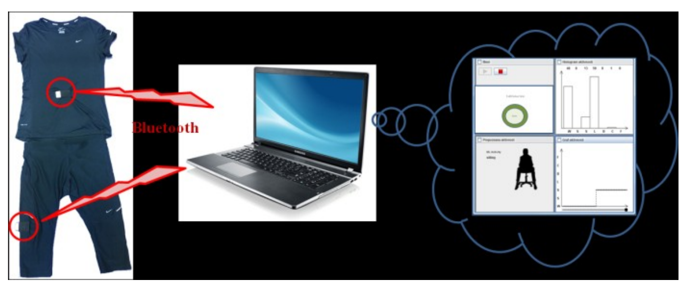

Fig. 1. The RAReFall system.

The placement of the sensors was chosen as a trade-off between the physical intrusiveness and the performance in preliminary tests [11][12]. The Shimmer accelerometer-sensor platform [13] was chosen because it has a reasonable battery life and compact size, is completely wireless, and has the option to reprogram the sensor's firmware based on the user's needs and situation. The platform has a 3-axis accelerometer, uses Bluetooth communication, and has 2 GB of storage, which is enough to store 3 months of sensor data when the frequency of acquisition is 50 Hz. This frequency proved sufficient to capture even the fastest human movement and was therefore used in our tests. The laptop is equipped with a long-range Bluetooth antenna in order to ensure the maximum reliability and signal strength.

III. 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., laptop. 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 $[t - 2\ \text{s}, t - 1\ \text{s}]$ interval, and the $[t - 1\ \text{s}, t]$ 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 $[t - 2\ \text{s}, t]$ interval. The system thus reports the user's activity and detects falls with a two-second delay.

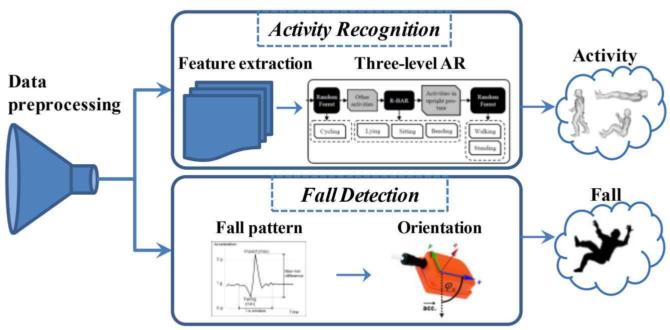

Fig. 2. The data and recognition flow in the RAReFall system.

In the following sections, the AR and FD methods are briefly described. More technical details can be found in our previous work, [14] for AR, and [15] for FD.

A. Activity Recognition

In the AR module, the activities are recognized by a three-level scheme [14]. 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.

B. 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 [15]. 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 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.

IV. Experiments

A. 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. The evaluation was performed on a complex, 90-minute scenario, recorded by 10 people. The 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.

Table I shows the offline performance of the RAReFall system on the pre-recorded dataset. The performance of the AR is high, achieving 99.04% 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 II) 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 I. RAREFALL SYSTEM - OFFLINE PERFORMANCE.

Performance	Activity Recognition	Fall Detection
Recall	99.22%	93.33%
Precision	98.85%	66.67%
F-measure	99.04%	77.78%

TABLE II. FALL DETECTION DETAILED RESULTS.

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

B. *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]. This competition evaluates AR systems in a living lab using several criteria:

- Recognition performance − how accurately the system recognizes the activities (including the falls).
- 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. Measured in minutes of work per person needed to complete the installation.
- Interoperability with AAL systems – the metrics used are: the use of open-source solutions, availability of libraries for development, integration with standard protocols.

The protocol of the competition was the following. First, each competitor installed their AR system in the living lab. Next, a volunteer performed a predefined scenario of everyday activities. The competing system, which was currently installed, tried to recognize the activities of the volunteer, including falls. The same procedure with the same scenario and same volunteer was repeated for each competing system. Eventually, each competing system was evaluated using the aforementioned criteria. The 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.

V. CONCLUSION

This paper and demo 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. 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. While sewing the sensors into clothing contributed to user acceptance, more work on ergonomics is needed. A smartphone implementation is also considered for future development.

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