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Evaluating Wearable Activity Recognition and Fall Detection Systems

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Abstract— **Activity recognition (AR) and fall detection (FD) research areas are very related in assistance scenarios but evolve independently. Evaluate them is not trivial and the lack of FD real-world datasets implies a big issue. A protocol that fuses AR and FD is proposed to achieve a large, open and growing dataset that could, potentially, provide an enhanced understanding of the activities and fall process and the information needed to design and evaluate high-performance systems.**

Keywords— **AAL, Activity recognition, Fall detection, inertial sensor.**

I. INTRODUCTION

Demographic tendencies in today's societies lead to gentrification of the population both in developed and developing countries as well as in third world countries. According to UNFPA[1] although currently only Japan has an older population of more than 30 per cent, by 2050, 64 countries are expected to join it. These countries are supporting Ambient Assisted Living (AAL) research programs that address ICT technologies for the independent living of elders and disabled [2].

To achieve this goal, two main pillars are needed: Activity Recognition (AR) and Fall Detection (FD).

AR is a research area where the objective is to recognize human activities. The automatic and unobtrusive identification of users activities is one of the challenging goals of context-aware computing [3] and is expected to be a practical solution to monitor aged people. AR can be focused on basic activities (lying, sitting, standing up, etc.) or in complex ones (watching TV, cooking, having a shower, etc.). AR can be a good feedback tool to advise the user, relatives or doctors about the accomplishment of rehabilitation, preventive exercises or specific activity goals such as get some number of steps a day.

FD can be defined as an assistive technology whose main objective is to alert when a fall event occurs. In a real-life scenario, it has the potential to mitigate some of the adverse consequences of a fall. Specifically, FD can have a direct impact on the reduction in the fear of falling and the rapid provision of assistance after a fall. In fact, falls and fear of falling depend on each other: an individual who falls may subsequently develop fear of falling and, viceversa, the fear of falling may increase the risk of suffering from a fall [4]. Fear of falling has been shown to be associated with negative consequences such as avoidance of activities, less physical activity, falling, depression, decreased social contact and lower quality of life.

According to the World Health Organization [5] more than 28% of people aged 65 and over fall each year increasing to more than 32% for those over 70 years of age. If preventive measures are not taken in the immediate future, the number of injuries caused by falls is projected to be a 100% higher in 2030. In this context, assistive devices that could help to alleviate this major health problem are a social necessity. Indeed, fall detectors are being actively investigated.

The rest of the paper is organized as follows: Section 2 gives an overview of how AR systems are being evaluated and compared each other, Section 3 reviews the same for FD. The proposal of a high replicable protocol to create an open, flexible, growing and community maintained AR and FD dataset is presented in sections 4. Section 5 draws the conclusions.

II. EVALUATING AR

AR using wearable sensors [6] allows monitor user exercises and activities or detect abnormal behavior. AR also supports independent living, the main focus of some European Projects [7].

AR is mature enough from datasets point of view: Multiple datasets can be found in UCI Machine Learning Repository composed by different Activities of Daily Living (ADL). However, since each research group use different hardware or place their sensors in different positions, not all the datasets are feasible to every system and comparisons between different AR systems is not possible. To solve this problem two solutions have been proposed:

- Software-based competitions with a high number of sensors where the systems can choose the preferred sensors close to his hardware configuration. AR Challenge OPPORTUNITY [8], is the best example: an extremely sensor-rich and activity-rich common dataset against which all participants benchmark their proposed activity recognition software. The dataset includes 72 body-worn, ambient, and object sensors, a very high number of activity instances (more than 2500 instances of gestures) labeled at various levels of abstractions, executed by multiple persons.

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- Live competitions or (hardware + software)-based competitions where the competitors are requested to install and run their systems during a set of benchmarks. This approach is more challenging because it is often the data-acquisition part (the sensors) that limits the systems' reliability and acceptability, and thus their real-life usability. EvAAL (standing for Evaluating AAL Systems through Competitive Benchmarking) AR track competition [9] is the only competition hold with these characteristics.

A. EvAAL Experience

The main objective of AR track is to evaluate AR systems intended to be used by the elderly in real life.

During the '12 and '13 competitions, the following seven activities were recognized: lying, sitting, standing, walking, bending, cycling on a stationary bike, and falling. Most of them were selected because they are common in daily life and thus recognizing them is the starting point for AR. Cycling was included because it is a recommended exercise for older people, while falling is a major health hazard for the elderly. All the activities were included in a scenario that lasted approximately 5 minutes. The scenario included actions of daily living (watching TV, working in the kitchen, bathroom activities, sleeping) and was repeated twice, with the better run by each competitor counting towards the final score. In order to get approximately the same ground truth for all the competitors, audio cues were played from a file to signal the actor as to which activity should be performed three seconds in advance, giving the actor the time to prepare for it. This ground truth was refined by an evaluator who followed the actor and used an Android phone with a custom application to mark the precise time-stamps of the activities. In the competition, there is no limitation to the number and type of devices comprising the competing ARS. The only constraint that ARS should satisfy is the compatibility with the physical limitations of the hosting living lab.

While the evaluation scenario was short and relatively simple, the impression of people involved was that it is a decent indicator or real-life performance. An elderly simulation kit helped emulate the movements of a >65 years old person. A longer and more complex evaluation (multiple days of real life) would be preferable, but too difficult and expensive to organize.

The competition was a good opportunity for discussion, resulting in valuable feedback to improve both the AR and FD systems and the competition.

B. AR Datasets information

- Type of activities reported: Simple activities (lying, sitting, standing, etc.) or complex activities (watching TV, working in the kitchen, bathroom activities, sleeping, etc.).
- Demographics information: number of participants and in some cases age, weight and height.
- Sensor information: sampling frequency and range, fixation site, number and type of sensors.
- Attribute information: Description of all the recorded attributes.

III. EVALUATING FD

Many different approaches have been explored to automatically detect a fall using inertial sensors [10]. The biggest problem of this research area is datasets. To the best knowledge of authors, there are only a few in the AmI repository [11,12] and in the EvAAL website [13] with simulated falls. Furthermore there are no public datasets with real falls a very important issue according Bagalà et al. work [14]: published algorithms report high sensitivity (SE) and high specificity (SP) being tested on simulated falls performed by healthy volunteers, but applying the same algorithms to a real fall database SP and SE average is considerably lower. For instance, the best one [15] provides 83% SE and 97% SP but the results are still different from those obtained by the authors on their simulated-falls database (100% SE and SP). Moreover, Kangas et al. [16] also found differences between simulated and real-world falls on beds in terms of low impact magnitude.

Without public real fall datasets it is difficult to evaluate and compare FD systems such as AR systems. Only projects working with "fallers" can compare different algorithms with his private databases.

According Schwickert et al. [17] only 6 of 96 studies from 1998 to 2012 were performed including real-world fall data. From these papers only one [18] reported more than 10 falls (n=20). So the private datasets reports less than 100 falls. Privacy issues and the analysis of FD from a biomedical point of view promote this lack of public real-world datasets.

A. FD Datasets information

- Type of falls reported: Forward falls, backward falls, mixed direction falls
- Context information: Location (indoor/outdoor), activity before the fall (standing, sitting, walking forward, walking backwards, sit-to stand, stand-to-sit, etc.), reported direction of fall (Forward, backward, sideward), Impact spot

(floor, against wall/locker before hitting the floor, bed/sofa, desk, etc.), mats thickness (if simulated) and soil type (if real or quasi-real).

- Demographics information: number of participants, age, weight, height, BMI, gait speed and in some cases balance [18].
- Sensor information: sampling frequency and range, fixation site, number and type of sensors.
- Attribute information: Description of all the recorded attributes.

IV. PROPOSAL

The difficulties to access to a group of high risk of falling patients, to report in a medical way the results (patient agreement, patient privacy, trial protocol approved by Ethics Committee, written informed consent before the trial, etc.) and to obtain a high number of falls is a chimeric task but we can support an open dataset of AR and FD in order to obtain a high number of simulated kind of falls and multiple kind of simple and complex activities accepted from both communities.

AmI repository and EvAAL achieved the first step, with datasets combining AR and FD but reported in an AR manner, missing some important points from FD point of view (Demographics, context).

To avoid the appearance of multiple datasets with different sensor, activities and falls configurations we defined a protocol focused on create an open and growing AR-FD dataset with multiple activities (simple and complex) and simulated and real falls. The main idea is to allow to other people replicate the data acquisition system. Due to the fact that current mobile phones include tri-axial accelerometers, gyroscopes and magnetometers and are 'wearable and ubiquitous devices' one or more will be used to acquire the data. How to attach to the human body the mobile phone(s) is capital. To avoid only one configuration all the positions will be detailed in the dataset so some features will be present and other no (assuming multiple contributors this will not be an issue). Our first trial includes a mobile on the hip and another on the chest (sternum) using a elastic-band. To avoid different inertial sensors' frequency rate depending on the mobile device, an Android application (we are developing the iOS one) captures data annotating the position of the sensors at a fixed rate (discarding the readings out of this rate) and generates the files. Currently we work with 20 Hz to allow the longer range of Android mobile devices.

According to FD and AR Datasets, some information such as gait speed, activities, reported direction of fall or mats thickness are hard to report from people out of medical or research environments. To simplify the reporting task, a video recording, time-stamped and synchronized to the acquisition data mobile phones must be included to the dataset. To simplify the time-stamped and synchronization process, another mobile phone is used to record the video through another application prepared for this task.

Community can complete the missing information analysing the video and even discard some not suitable events (e.g. not realistic simulated falls).

To add instances to the dataset, contributors will upload the video and the generated files to a server. A visual description of the infrastructure is shown in Figure 1.

We hope to publish the initial instances in the dataset June 2014.

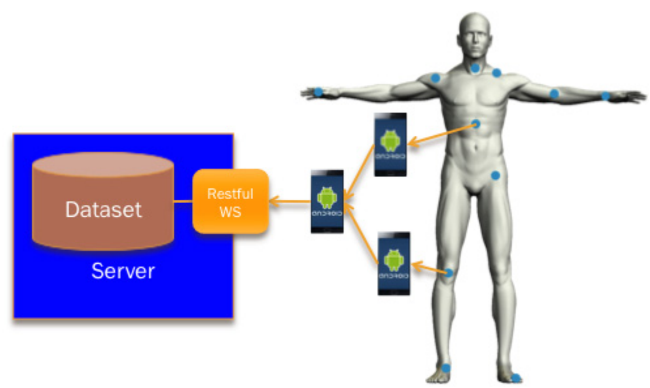

Fig. 1 Infrastructure used to collect the dataset

V. CONCLUSIONS

Fusing FD and AR, including rehabilitation exercises within the recognized activities, must support active independent living in aged people. To achieve this fusion some challenges must be complete:

1. Having public datasets in realistic environments with a rich configuration of sensors and a good description of users, sensors, activities and falls and environment
2. Evaluate multiple algorithms or systems through live competitions or new and independent datasets.

Although the EvAAL-AR competition is a good example of how to evaluate different hardware and software approaches with the same goal, participating in the competition requires an investment in time and money and only teams that were confident in the quality of their system participated, only four competitors each year.

Bagalà et al. approach is cheaper for "competitors" but it is time consuming for organizer: implementing all the algorithms (AR algorithms are usually more complex FD ones) and applying them to an independent and real fall database. Furthermore data collection must be prepared to consider diverse AR and FD sensor location configuration.

Our proposal, a high replicable protocol to create an open, flexible, growing and community maintained dataset of multiple activities and simulated or real falls could allow a software competition based on multiple hardware configurations using diverse positions of the acquisition tools, the mobile phones.

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CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

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