Demo Abstract: Demonstration of the FABER System for Fine-grained Recognition of Abnormal Behaviors

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***Abstract*—The life expectancy is rapidly growing in many countries. According to the United Nations, the percentage of elderly population will rise from 5% in 2013 to 11% in 2050. The increasing aging of the population implies an increase of age-related diseases, and an increase in terms of health-care costs. The innovations introduced by pervasive computing, and in particular by sensor-based activity monitoring methods, can be exploited to early detect the onset of health issues. For this reason, we devised a novel method to recognize anomalies that a senior performs during the execution of activities of daily living, based on data acquired from unobtrusive sensors deployed at home. The objective is to support the clinicians in the early diagnosis of neurodegenerative diseases, providing them with fine-grained information about abnormal behaviors. In this paper, we present a demonstration of the method, based on a graphical tool that simulates the execution of activities and abnormal behaviors of an elderly person in a sensor-rich smart home.**

I. Introduction

Mild Cognitive Impairment (MCI) is defined as a transitional stage between normal aging and dementia [1]: it reflects the clinical situation where a person presents losses of memory and objective evidences of cognitive impairment, but no sign of dementia. There are evidences of differences in performing Activities of Daily Living (ADLs) among MCI patients compared to healthy elderly people and individuals affected by dementia [2]. The conventional clinical methods for diagnosing cognitive disorders are commonly based on observation (by clinicians or caregivers) of execution of various ADLs by the patient [3]. However, this episodic clinical examination method is not sufficient for the optimum diagnosis of the disorder, particularly at an early stage. The main issue of this approach is that the patient is not continuously observed and some symptoms can be imperceptible at the time of medical examination. Therefore, it is imperative to develop technologies capable to monitor the daily routine of such persons over long time periods and in an unobtrusive manner. In order to solve the above-mentioned problem, we proposed FABER, a system for Fine-grained Abnormal BEhavior Recognition. FABER supports the clinicians in the early diagnosis of neurodegenerative diseases, providing them with fine-grained descriptions of the anomalies occurred during the execution of ADLs by a patient in his/her home. An unobtrusive ambient sensor network deployed in patient's home is in charge of monitoring his/her interaction with the environment. Low-level data from the sensors are then analyzed by an hybrid statistical-symbolical reasoning framework in order to recognize ADLs and anomalies performed by the patient. The fine-grained information of detected abnormal behaviors is then communicated to the clinicians, that analyze it using a dedicated reporting tool. In this paper, we present a demonstration of the framework, based on a graphical tool that simulates the execution of activities and abnormal behaviors of an elderly person in a sensor-rich smart home. The paper is organized as follows. Section II briefly illustrates the FABER system. Section III illustrates our proposal of demonstration for the PerCom conference. Section IV concludes the paper indicating the directions of future work.

II. The FABER system

The objective of the FABER system [4] is to recognize, for a particular patient, the anomalies that occurred during the execution of ADLs inside his/her home at a fine-grained level. FABER relies on models of abnormal activity routines that may indicate the onset of early symptoms of MCI. These models are chosen through the collaboration with cognitive neuroscience experts. A unobtrusive sensor network deployed in the patient's home is in charge of acquiring low-level information about the interaction of the patient with the environment. Acquired data is used to recognize the performed ADLs and the occurred anomalies. The result of the inference is then communicated to the medical center and shown in a dashboard to support the clinical diagnosis.

A. Data acquisition

The patient is monitored using a sensor based infrastructure deployed in his/her home. Various kinds of sensors are installed on various household items, including:

- PIR sensor to detect the presence of the patient in a particular place of the home;
- Magnetic sensor to detect opening and closing of door and cabinets;
- RFID tags to monitor when the patient interacts with objects like medicine boxes and food packages;
- Temperature sensor to monitor the usage of the stove;
- Pressure sensor to monitor if the patient is sitting on a chair.

In order to better recognize activities and anomalies, low-level detections need to be post-processed. First of all, noisy sensors measurements (i.e. repetitive detections of PIR sensor in short time) are removed or aggregated. Then, a semantic description of the simple actions performed by the patient (i.e. "the patient has retrieved medicine M1 from the medicine cabinet") is derived from the acquired raw sensor data.

B. Hybrid reasoning

The simple actions derived by the semantic integration of raw sensor data are used to recognize the performed ADLs (e.g. taking the medicines, cooking, ...) and anomalies (e.g. taking a wrong medicine, forgetting to eat a meal, ...). For this purpose, an hybrid probabilistic and symbolic reasoning framework is used.

1) Activity recognition: Activities are recognized using Markov Logic Network [5], a probabilistic logic that unifies statistical and logical reasoning. A set of weighted rules is used to infer the most probable activities performed by the patient using Maximum a-posteriori inference. The weights of the rules are learned through a training set of activities.

2) Anomaly recognition: A knowledge-based inference engine is used to infer the abnormal behaviors of the patient. Anomalies are defined with first-order logic rules that consider both the recognized activities, including all the simple actions involved, and specific information about the patient (e.g., medicine prescriptions).

C. Reporting

The results of the recognition algorithms are communicated to the back-end of the hospital center where the data are stored. The clinicians can inspect the recognized activities and anomalies by accessing a dedicated web dashboard. This dashboard is a reporting tool useful to support clinicians in analyzing the symptoms of behavioral modifications over time [6]. The dashboard also offers different plots that show the temporal trend of occurrence of anomalies.

III. Demonstration

In this section we illustrate the demonstration of the FABER system.

A. Visual simulation

We experimented the effectiveness of FABER in a smart lab and in the home of a real patient; however, we cannot reproduce the smart home environment at the PerCom demo venue. Hence, we decided to perform the demo taking advantage of Siafu [7], a graphical simulation tool to visualize the behavior of agent in smart spaces. We designed different simulations of the behavior of an hypothetic patient inside her home, making her perform some plausible sequences of actions during a typical day. We also simulate various ambient sensors that produce low-level data according to the user's actions and movements. Figure 1 illustrates a screenshot of the simulation's GUI. The graphical user interface (GUI) depicts a 2D map of the smart-home, showing the various rooms and household items. The GUI shows the patient (represented by a stick man/woman) moving in the environment and performing daily activities interacting with the environment. Besides the map of the smart-home, the GUI shows also a panel (on the right) that contains:

- date and hour of the simulation;
- a slide bar that can be used to speed up or slow down the time;
- static information of the person (name, medical prescriptions, ...);
- dynamic information of the person (position, current action performed).

B. Structure

During the demo, the simulation is displayed on a dedicated screen, while a different screen shows the real-time log of the sensors events produced according to the person's activities (Figure 2).

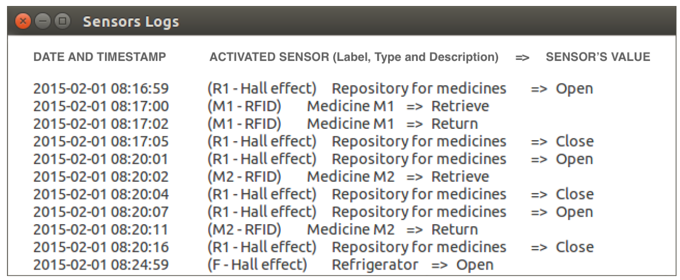

Fig. 2. The sensors logs produced real-time by the simulation

The combination of the two interfaces illustrates the data acquisition in the system. At the end of the simulation, the acquired data are used by FABER algorithms to recognize ADLs and abnormal behaviors. The inference result are shown by the FABER Web dashboard. While our tool can visualize randomly generated sequences of actions, for the sake of the demonstration we defined predefined sequences of actions performed by the patient in the two cases.

1) The patient performs a set of different ADLs and no anomaly occurs. This part is used to illustrate the activity recognition method based on the detected sensor events.
2) The patient performs a set of different ADLs and some anomalies occur. In this part we illustrate the anomaly recognition method based on the recognized activities.

C. Storyboard part A - Activity recognition

The simulation begins at 7.55 a.m., the person/agent is sleeping in her bed and at 8.00 a.m. she wakes up. Initially she goes to the bathroom and then she comes back to the bedroom and dresses up. In the meantime, the GUI is briefly described, and the functionalities of the right panel are shown. Then the sensors logs window is opened and described. The agent goes to the dining room and takes the prescribed medicines, then she moves to the kitchen and begins to prepare breakfast. After finishing preparing it, she consumes breakfast by sitting at the kitchen table. During these ADLs we show how the agent

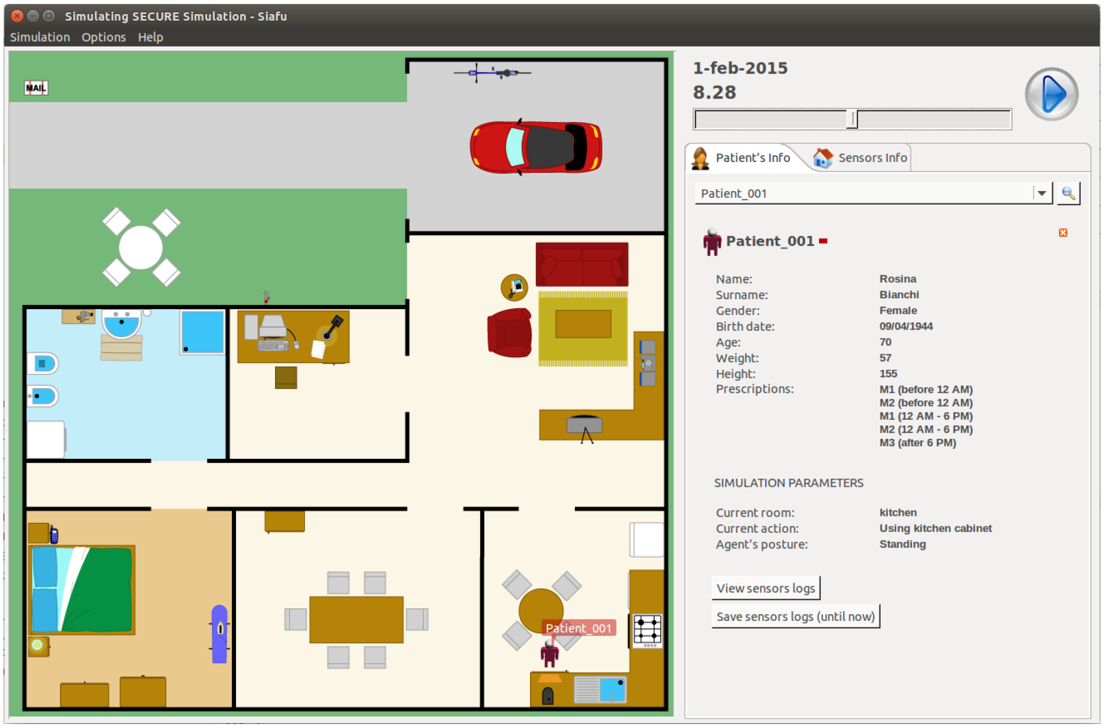

Fig. 1. Our simulation tool

actions determine the sensor readings, shown in the sensors logs window. The estimated time of this part is 2 minutes, without pausing or changing the speed of the simulation. Finally, we compare the recognized ADLs (shown in the dashboard) with the log of the actual activities performed by the agent, and we briefly explain the activity recognition algorithm, showing the MLN rules used by FABER.

D. Storyboard part B - Abnormal behavior recognition

In this second part, the person still wakes up at 8.00 a.m., then she goes to the bathroom, dresses up and takes some medicine; but this time she takes a medicine that was not prescribed. Later, she goes to the kitchen and prepares the breakfast. After that, she starts setting up the table, repeatedly executing some actions (e.g., retrieving and returning objects from the kitchen cabinets), without completing the activity. Then, she leaves the kitchen without consuming the breakfast. In this case the system detects two anomalies: taking a wrong medicine and skipping eating breakfast. The estimated time is 2 minutes also for this second part. Finally, we compare the recognized anomalies (shown in the dashboard) with the log of the actual anomalies performed by the agent, and we explain the abnormal behavior detection algorithm, showing the rules used by our system.

IV. Future Work

There are many directions to improve our simulation tool by making it more modular and customizable in terms of smart spaces represented, sensors deployed, performable actions and activities. Another direction is to use the tool for graphically visualizing the actual patient's behavior based on sensor data coming from the sensors, as well as recognized activities and anomalies. That functionality can be useful to simplify the annotation of the dataset for the training phase, avoiding the presence of human observers or use of cameras. Moreover, that functionality could be exploited by clinicians to better understand the patient behavior at a particular moment (e.g., when an anomaly is detected).

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