

# Fine-grained Recognition of Abnormal Behaviors for Early Detection of Mild Cognitive Impairment

Daniele Riboni\* Claudio Bettini\* Gabriele Civitarese\* Zaffar Haider Janjua\* Rim Helaoui<sup>◊</sup>

\*Università degli Studi di Milano, Dept. of Computer Science, EveryWare Lab

<sup>◊</sup>University of Mannheim, Research Group Data & Web Science

Email: {daniele.riboni, claudio.bettini, gabriele.civitarese, zaffar.janjua}@unimi.it, rim@informatik.uni-mannheim.de

**Abstract**—According to the World Health Organization, the rate of people aged 60 or more is growing faster than any other age group in almost every country, and this trend is not going to change in a near future. Since senior citizens are at high risk of non communicable diseases requiring long-term care, this trend will challenge the sustainability of the entire health system. Pervasive computing can provide innovative methods and tools for early detecting the onset of health issues. In this paper we propose a novel method relying on medical models, provided by cognitive neuroscience researchers, describing abnormal activity routines that may indicate the onset of early symptoms of mild cognitive impairment. A non-intrusive sensor-based infrastructure acquires low-level data about the interaction of the individual with home appliances and furniture, as well as data from environmental sensors. Based on those data, a novel hybrid statistical-symbolical technique is used to detect first the activities being performed and then the abnormal aspects in carrying out those activities, which are communicated to the medical center. Differently from related works, our method can detect abnormal behaviors at a fine-grained level, thus providing an important tool to support the medical diagnosis. In order to evaluate our method we have developed a prototype of the system and acquired a large dataset of abnormal behaviors carried out in an instrumented smart home. Experimental results show that our technique has a high precision while generating a small number of false positives.

## I. INTRODUCTION

Several recent studies show that the proportion of elderly people over the whole population is rapidly growing in most countries. For instance, the European old-age dependency ratio (i.e., the ratio of people aged 65 years or older to people aged 15-64 years) is projected to double in the next decades [1]. As a consequence, a growing portion of people is at high risk of experiencing non communicable diseases, frailty and social exclusion, and may need long-term care, including nursing at home or frequent hospitalization. Of course, the inability of living independently may not only spoil the quality of life of elderly people and of those caring for them, but will also challenge the sustainability of the entire health system. Hence, there is a growing interest in exploiting pervasive computing technologies to support independent living and healthcare, especially for the senior population.

In this paper we propose a novel method to support early detection of mild cognitive impairment (MCI) for elderly people living independently at home. In the medical literature, MCI is used as a clinical diagnosis to describe a transitional state between healthy cognitive ageing and dementia, characterized by preserved functional abilities [2]. According to

the criteria proposed by the International Working Group on MCI, there are evidences of subtle differences in performing instrumental activities of daily living (IADLs) among MCI patients compared to both healthy older adults and individuals with dementia [3]. Hence, long-term monitoring of daily living activities and recognition of abnormal behaviors may help practitioners to early detect the onset of cognitive impairment.

Different scales have been proposed to assess the cognitive health of people based on questionnaires and interviews about the ability of performing various kinds of IADLs [4]. However, that approach is prone to reporting bias; moreover, it cannot be applied to continuously monitor the cognitive health of a large number of people, since it incurs evident overheads in terms of time, resources and monetary costs. A few previous works, reviewed in Section II, have tried to detect behavioral markers of MCI onset through pervasive computing technologies, obtaining significant correlation between the predicted and actual cognitive status of the patient. However, those works have different limitations. Some of them require the execution of ability tests about the performance of IADLs in an instrumented smart home of a hospital; hence, they incur high costs and cannot be applied on a continuous basis. Other works rely on continuous monitoring of low-level behavioral markers (steps taken, walking speed...). While potentially useful to trigger alarms about possible MCI onset, those markers do not provide specific support to the diagnosis, since they do not report fine-grained descriptions of the anomalies occurred during the execution of IADLs.

In order to overcome the limitations of existing techniques we propose FABER, a novel technique for Fine-grained Abnormal Behavior Recognition. Our method relies on medical models describing abnormal activity routines that may indicate the onset of early symptoms of MCI. These models have been acquired through the collaboration with cognitive neuroscience experts of a leading center for care and research on neurodegenerative disorders. A non-intrusive sensor-based infrastructure is deployed at the patient's home, which acquires low-level information about the interaction with home appliances and furniture, as well as environmental parameters. Based on sensor data, we first detect the general activity being performed by the subject and then recognize *anomalies* in performing that activity or a group of activities. They include inappropriate timing and unnecessary repetitions of subactions, but also high level observations like “irregularly

assuming meals” or “often consuming cold meals”. We use a hybrid statistical-symbolical technique including supervised learning, rule-based reasoning and probabilistic reasoning. Abnormal behaviors are communicated to the medical center for further analysis and interpretation. Differently from previous works, our method can be applied continuously at the patient’s home and, thanks to symbolic reasoning postprocessing over recognized activities, abnormal behaviors can be detected at a fine-grained level. In order to evaluate our approach, we have developed a prototype of our system, and collected a large dataset from an instrumented smart home. Experimental results show that our technique is able to detect most of the abnormal behaviors that we have targeted while producing a small number of false positives.

The rest of the paper is structured as follows. Section II discusses related work. Section III presents the FABER method. Section IV briefly summarizes experimental results. Finally, Section V concludes the paper.

## II. RELATED WORK

Several studies in the neuropsychology research field show that it is possible to distinguish between cognitively healthy adults and cognitively impaired individuals based on subtle differences in their behavioral patterns [3]. There is a growing interest in exploiting pervasive computing technologies to automatically capture and measure those differences [5]. For instance, a sensor-based infrastructure has been used to unobtrusively monitor the execution of IADLs by older adults in a smart-home [6]; the results have shown a significant correlation between the cognitive health status of the subject and the level of assistance that he needed in order to complete the activities. More recently, motion sensors and contact sensors have been used in [7] to measure low-level activity patterns, such as walking speed and activity level in the home; results have shown that the coefficient of variation in the median walking speed is a statistically significant measure to distinguish MCI subjects from healthy seniors.

Based on this line of research, a few works have proposed to apply artificial intelligence methods on data acquired in sensor-rich environments, for assessing the cognitive health status of an individual performing a fixed set of predefined activities. In the work of Dawadi et al. [8], patients were invited to execute a list of routines (e.g., write a letter, prepare lunch) inside a hospital smart-home. Different kinds of sensors were used to detect movements inside the home and to track the use of furniture and appliances. Based on data coming from the home sensors, machine learning methods were used to assign a score to each performed activity; the score measures the ability of the subject to perform the activity correctly. The achieved scores were then used to predict the cognitive status of the patient (cognitive health or dementia). However, experimental results showed a not completely satisfactory degree of correlation among the predicted scores and the ones assigned by a human observer. In general, the low correlation may be due to the intrinsic difficulty of capturing the variability of human behaviors from a corpus of training data. In this work,

we take a different approach: we use supervised learning only to detect the start- and end-times of activities, while we rely on domain knowledge provided by neuroscience experts to recognize the actual anomalies. To the best of our knowledge, our work is the first one that tries to apply this approach to cognitive health assessment.

The supervised learning approach has been applied in other works, including [9], [10], using other learning methods. A further difference with those works is that they assume that the patient executes a predefined set of IADLs following the instructions of practitioners in a medical center, while our method is intended to run continuously at the patient’s home, and does not interfere with the normal behavior of the patient.

Finally, we mention that several research efforts have been made to automatically detect abnormal behaviors for surveillance applications. Typically, in that field, abnormal actions are recognized based on the analysis of audio and video and on the application of machine learning techniques [11]. However, audio- and video-based systems are not suitable to our problem due to obvious privacy issues. Moreover, surveillance systems are mainly targeted to low-level physical actions, such as assaults, fights, stealing of objects, while our goal is to monitor high-level daily living behaviors, which are subject to high variability of execution based on the characteristics of the specific individual, on the environment and on many other contextual conditions.

## III. THE FABER HYBRID TECHNIQUE

In this section we illustrate the *Fine-grained Abnormal Behavior Recognition (FABER)* hybrid technique to support early detection of MCI.

### A. Recognition framework

In Figure 1 we show the recognition framework. The system is implemented at the elderly’s home. A smart-home monitoring system running on a mobile device (e.g., a tablet) is in charge of executing the FABER algorithms. Different sensors, including environmental sensors, presence sensors, and RFID readers, are attached to furniture and instruments, and communicate raw data to the SEMANTIC INTEGRATION LAYER. That layer is in charge of using raw sensor data to detect simple actions (e.g., “the fridge door has been opened”) and other events (e.g., “the temperature in the kitchen is more than 30 degrees Celsius”). Actions and events, together with their timestamps, are communicated to the MARKOV LOGIC NETWORK (MLN) REASONER using a shared vocabulary. The reasoner periodically (e.g., daily) analyzes the event logs and infers the start/end time of activities based on the received data. The inferred activity boundaries are communicated – together with actions and events – to the KNOWLEDGE-BASED INFERENCE ENGINE. The inference engine evaluates the rules modeling abnormal behaviors, which are extracted from a medical knowledge base of MCI models and indicators. Finally, detected abnormal behaviors are communicated to the hospital center for further analysis by the doctors.

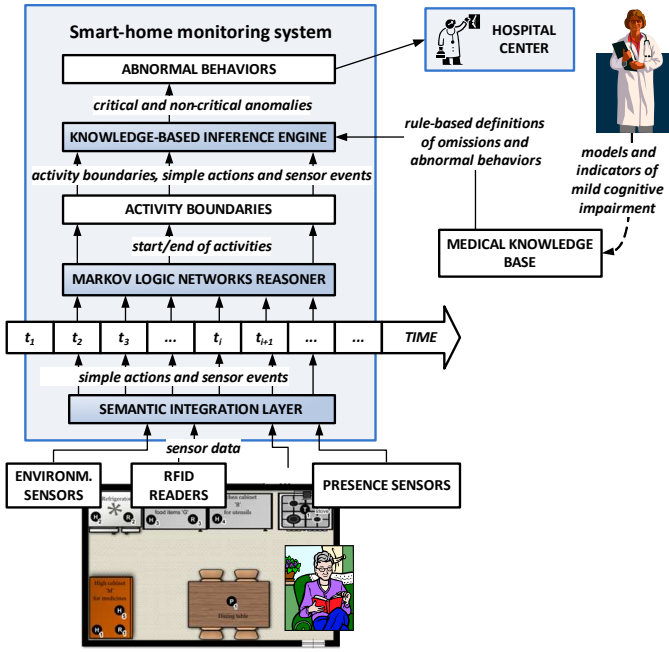


Fig. 1. Recognition framework

### B. Semantic integration of sensor data

The SEMANTIC INTEGRATION LAYER is in charge of acquiring raw sensor data and to use them for inferring semantic descriptions of the current context, which are exploited by the MLN reasoner to detect the activity boundaries. Depending on the kind of available sensors, that module applies simple inference methods to derive basic actions and events. For instance, a rule states that “if the presence sensor detects a presence near the kitchen table, and the sensor on the kitchen’s chair detects a weight higher than 50Kg, then the current action is *sitting at the kitchen chair*”. Timestamped actions and events are represented using a shared vocabulary and communicated to the MLN reasoner.

### C. Detection of activity boundaries

After presenting our temporal model, we illustrate Markov Logic Networks (MLN) and we explain how we use this probabilistic logic to detect activity boundaries. More details about our method can be found in [12].

1) *Temporal model*: Suppose that, in our system, the following temporal sequence of sensor events occurs:

$$\langle event(e_{j_1}, t_1), event(e_{j_2}, t_2), \dots, event(e_{j_m}, t_m) \rangle,$$

where  $event(e_{j_i}, t_i)$  indicates that the sensor event  $e_{j_i}$  occurred at time instant  $t_i$ . For the sake of this work, we assume that sensor nodes communicate their sensed events in real-time to a gateway. The gateway is in charge of assigning a unique timestamp to each event, based on the time at which it is received. Hence, we impose a total order on event timestamps  $\langle t_1, t_2, \dots, t_m \rangle$ .

2) *MLN*: Temporal sequences of sensor events can be ambiguous to interpret, since the same sequence can result from the execution of different and possibly mutually exclusive activities.

*Example 1*: Consider the following first-order logic (FOL) knowledge base:

$$\forall a, e_j, e_k, t_i, t_{i+1} \text{ event}(e_j, t_i) \wedge \text{ event}(e_k, t_{i+1}) \rightarrow \text{currentActivity}(a, t_i). \quad (1)$$

$$\forall t \text{ currentActivity}(\text{SetTheTable}, t) \rightarrow \neg \text{currentActivity}(\text{WashDishes}, t). \quad (2)$$

Formula (1) states that the temporal sequence of two sensor events  $e_j$  and  $e_k$  occurring at  $t_i$  and  $t_{i+1}$ , respectively, indicates the execution of an activity  $a$  at  $t_i$ . Formula (2) states that the current activity of an individual cannot be “set the table” and “wash dishes” at the same time instant. Suppose to instantiate event  $e_j$  to *ClosingSilverwareDrawer* and  $e_k$  to *OpeningGlasswareCabinet*. The rules below, obtained by grounding formula (1), encode the fact that the occurrence of the temporal sequence  $\bar{s} = \langle event(\text{ClosingSilverwareDrawer}, t_i), event(\text{OpeningGlasswareCabinet}, t_{i+1}) \rangle$  can indicate both activities “set the table” and “wash dishes” at  $t_i$ :

$$\text{event}(\text{ClosingSilverwareDrawer}, t_i) \wedge \text{event}(\text{OpeningGlasswareCabinet}, t_{i+1}) \rightarrow \text{currentActivity}(\text{SetTheTable}, t_i). \quad (3)$$

$$\text{event}(\text{ClosingSilverwareDrawer}, t_i) \wedge \text{event}(\text{OpeningGlasswareCabinet}, t_{i+1}) \rightarrow \text{currentActivity}(\text{WashDishes}, t_i). \quad (4)$$

However, the derivation of both activities as instances of *currentActivity* at the same time instant  $t_i$  would violate formula (2), making the model inconsistent.

The main idea of Markov logic [13] is to allow FOL formulae to be “softened”. The validity of a soft formula is evaluated according to the probability of being true with respect to a set of axioms describing reality. Each soft formula is associated to a *weight* that represents the confidence on the validity of the formula. Weights are generally learned from a training set of observations. The main inference task of MLN reasoning is to determine the most probable set of axioms representing reality that can be inferred based on the defined formulae and a set of observations. Intuitively, formulae with higher weight will have higher influence in deriving these axioms.

*Example 2*: Referring to Example 1, MLN can solve the described problem by assigning formula (1) to the set of soft formulae and formula (2) to the set of hard formulae. The actual weights for the instantiations of formula (1) are estimated through supervised learning on a training set. Suppose that the estimated weight of formula (3) is higher than the one of formula (4) since, in the training set, the sensor event sequence  $\bar{s}$  is more frequently observed during “set the table” than during “wash dishes”. In that case, if  $\bar{s}$  is observed, the MLN reasoner would infer that the most probable *currentActivity* at

$t_i$  is “set the table”. The MLN reasoner cannot derive both activities, since this would violate the hard formula (2). Of course, in order to effectively recognize the current activity, we need to use multiple formulae involving complex sequences of sensor events.

3) *Detecting activity boundaries through MLN*: In our model, the observations correspond to the sensor events. Predicate  $nextEvent(t_i, t_{i+1})$  indicates that the sensor event occurred at time  $t_i$  occurred before the one at  $t_{i+1}$ , and no other sensor event occurred between them. As explained in Section III-C2, in our architecture we ensure that no more than one sensor event can occur at a given time instant. Other predicates correspond to the activity boundaries:  $startActivity(a, t)$  indicates that activity  $a$  begins at time  $t$  and  $endActivity(a, t)$  indicates that activity  $a$  ends at time  $t$ . The approach used for boundary recognition, initially proposed in [14], is to write appropriate soft formulae to create a correlation between windows of  $n$  consecutive sensor events and start/end of activities. For example, for  $n = 2$  we use the following soft formulae:

- $event(+e_1, t_1) \wedge event(+e_2, t_2) \wedge nextEvent(t_1, t_2) \rightarrow startActivity(+a, t_1)$
- $event(+e_1, t_1) \wedge event(+e_2, t_2) \wedge nextEvent(t_1, t_2) \rightarrow endActivity(+a, t_2)$

The  $+$  symbol before a variable means that a weight is learned for each grounding of that variable. For each couple of consecutive sensor events, the first one of the above formulae correlates the first event with the start of an activity; the second formula correlates the second event with an activity end. The most effective value of  $n$  depends on the characteristics of the pervasive system and on the considered activities. In our work, we experimentally choose the optimal value of  $n$  (more details can be found in [12]).

We use hard formulae to express common sense knowledge about activity boundaries. For instance, in order to specify that it is impossible that an activity starts and ends at the same time, the following hard formulae are declared:

- $startActivity(a, t) \rightarrow \neg endActivity(a, t)$
- $endActivity(a, t) \rightarrow \neg startActivity(a, t)$

The weights of the soft formulae are learned using a training set of sensor events acquired during the execution of the considered activities. Soft formulae with learned weights and hard formulae are then used to compute *MAP* inference [13] on new data coming from the SEMANTIC INTEGRATION LAYER.

#### D. Modeling abnormal behaviors

As anticipated, our method relies on medical models of abnormal behaviors that may indicate the onset of MCI. In order to acquire those models, we collaborated with cognitive neuroscience experts from the Institute Fatebenefratelli<sup>1</sup>, Lombardy – a leading center in the field of mental health research and research on neurodegenerative disorders – within the SECURE<sup>2</sup>

<sup>1</sup>IRCCS (Research and Care Institute) St John of God Clinical Research Centre, Brescia – <http://www.irccs-fatebenefratelli.it>

<sup>2</sup>SECURE: Intelligent System for Early Diagnosis and Follow-up at Home, <http://secure.evlab.di.unimi.it/>

research project funded by Lombardy region and MIUR Italian ministry. Those anomalies have been selected during different project meetings among the technical and medical partners of the project, based on the medical practice and relevant literature [4]. In this work, we have considered anomalies related to food preparation, food consumption, and compliance to medical prescriptions. The anomalies are defined in natural language by the clinicians; e.g., “an anomaly occurs when the patient prepares a meal but forgets to consume it”.

In our model, each IADL consists of a sequence of simple actions, which we call “steps”. For instance, a patient could perform the IADL “taking medicines” by executing this sequence of steps: open the medicine repository, retrieve the medicine box, return the medicine box, close the medicine repository. We classified anomalies in the two categories:

- Non-critical anomaly. An anomaly is considered as non-critical when the patient skips a relevant step while performing a IADL, or spends too much time to perform the activity, but still he is able to complete the activity correctly. For instance, we consider a non-critical anomaly to occur when the patient forgets to close a repository after taking something from it. Non-critical anomalies can be considered as minor indicators of possible cognitive disorders, only if they occur more frequently than expected, or if their temporal trend significantly increases with time.
- Critical anomaly. A critical anomaly occurs when the patient skips some necessary step while performing an activity, forgets to execute a required activity, or performs the activity more times than expected. Critical anomalies are stronger indicators of possible MCI onset. These anomalies are further divided into four categories:
  - Omission: there are some steps in each IADL which are necessary and it is mandatory for the patient to perform them in order to complete the activity correctly: a critical omission occurs when the patient skips any of such steps. For instance, a critical omission related to the activity “taking medicines” is: “the patient forgets to retrieve the prescribed medicine during the prescribed time”.
  - Replacement: this anomaly occurs when, during a IADL, a patient replaces a correct step with a wrong one; for instance, “the patient has placed the butter inside a non-refrigerated cabinet”.
  - Wrong activity: it occurs when the patient performs an activity that should not be done. For instance, this anomaly occurs when the patient takes a medicine that was not prescribed.
  - Repetition: this anomaly occurs when the patient repeats the same activity more times than expected; for instance, when the patient consumes the morning breakfast twice in a day.

However, human behaviors are characterized by wide variability; factors such as contextual conditions, individual habits and personality traits may determine the execution of various anomalies that are not necessarily due to cognitive impair-

TABLE I  
EXAMPLES OF RULES MODELING ABNORMAL BEHAVIORS

No.	Rule	Anomaly type
1	$anomaly(cr, fridge, T_1) \leftarrow action(return, RF, S, T_1) \wedge action(close, door, S, T_2) \wedge RefFood(RF) \wedge NonRefStorage(S) \wedge (T_1 < T_2).$	Critical replacement: the patient has placed a food item that needs refrigeration inside a non-refrigerated cabinet.
2	$anomaly(nca, prepBF, T_1) \leftarrow startActivity(prepareBreakfast, T_1) \wedge endActivity(prepareBreakfast, T_2) \wedge ((T_2 - T_1) > 45minutes).$	Non-critical anomaly: the patient spent too much time to prepare breakfast.
3	$anomaly(co, medicine, null) \leftarrow prescribed(M, T_1, T_2) \wedge not((action(retrieve, M, C, T) \wedge MedCabinet(C) \wedge (T_1 < T < T_2)).$	Critical omission: the patient has not retrieved a prescribed medicine in due time.
4	$anomaly(wa, medicine, null) \leftarrow not(prescribed(M, T_1, T_2)) \wedge action(retrieve, M, C, T) \wedge MedCabinet(C) \wedge Medicine(M).$	Wrong activity: the patient has taken a medicine that was not prescribed.

ment. This is especially true for non-critical anomalies, as leaving repositories open, which may be normally done by cognitively healthy people for negligence or hastiness. Hence, the considered anomalies are not intended to provide an automatic diagnosis of the patient’s cognitive status. For instance, consider the example of *wrong activity* given above: the fact that the patient takes a medicine that was not prescribed is critical if he does it unintentionally (e.g., for a memory disorder). In other cases it may be a normal behavior; e.g., if the patient intentionally takes an over-the-counter drug that does not interfere with his medical prescriptions. Therefore, the frequency of detected anomalies and their temporal trend are used as a mean to trigger alarms to the practitioners for further inspecting the history of detected anomalies and their fine-grained descriptions.

In order to automatically reason with anomalies, we represent them as rules in propositional logic. The anomalies are represented by the predicate  $anomaly(Categ, Obj, Time)$ .  $Categ$  defines the category of the anomaly.  $Obj$  defines the objects or activities involved in the anomaly; for example, in case of a critical omission, the missed medicine may be the object related to that anomaly.  $Time$  defines the time (e.g., day, or exact instant) at which the anomaly has happened. Table I shows the representation of a few anomalies. The semantics of *not* is the one of *negation as failure*. Predicate  $prescribed(m, t_1, t_2)$  states that the patient must take medicine  $m$  from time  $t_1$  to time  $t_2$  of the current day.  $Medicine(o)$  (resp.  $Food(o)$ ) states that object  $o$  is a medicine box (resp. food item).  $Action(a, o, o', t)$  states that the patient executed action  $a$  on objects  $o$  and  $o'$  at time  $t$ .  $Holds(s, o, t_1, t_2)$  states that the status of object  $o$  has been “ $s$ ” from  $t_1$  to  $t_2$  (for instance, “the microwave oven has been on from 11:30 to 11:55”). The Holds predicate allows us to express temporal conditions that are useful in the definition of different anomalies. Temporal expressions that we use in our rule-based definitions include the interval of time during which an action is performed, the temporal distance between two actions, the temporal duration of an activity, the temporal order among activities.

#### E. Recognizing abnormal behaviors

Abnormal behaviors are recognized by an inference engine, which periodically (e.g., at the end of each day) evaluates the rule-based anomaly definitions considering the data acquired and inferred during the considered time period: activity

boundaries, actions and sensor events, as well as external knowledge including the medical prescriptions of the patient and the classification of objects in categories. Those data are represented by the predicates introduced in Section III-D, and added to the propositional logic knowledge base.

*Example 3:* Consider an elderly person living independently at home. Suppose that furniture and devices, including food cabinets and the fridge, are equipped with a magnetic sensor to detect the *open* and *close* actions. An RFID tag is attached to some food boxes to identify their content (e.g., rice, milk, coffee, sugar). RFID readers in the proximity of the cabinets and fridge are in charge of detecting which item has been retrieved or returned. Suppose that at 08:05 AM the patient opens the fridge  $f$  and retrieves the milk box  $m$  to prepare breakfast. Then after a few minutes he mistakenly puts the milk box in the non-refrigerated food cabinet  $c$  and closes its door. Hence, based on the sensed events, the following axioms are automatically added to the knowledge base:

$action(open, door, f, 8:05:00 AM).$   
 $action(retrieve, m, f, 8:05:07 AM).$   
 $action(return, m, c, 8:12:30 AM).$   
 $action(close, door, c, 1:12:35 AM).$

Since the knowledge base contains the axioms  $RefFood(m)$  (stating that the milk box contains a food item that must be kept refrigerated) and  $NonRefStorage(c)$  (stating that  $c$  is a non-refrigerated storage), rule 1 in Table I fires, recognizing an abnormal behavior.

#### IV. EXPERIMENTAL EVALUATION

Dataset acquisition and experimental evaluation are extensively reported in [12]; in the following we summarize the main findings.

A prototype implementation of the whole system has been developed in Java within the activities of the SECURE project. We have instrumented a kitchen in a smart home lab using different kinds of sensors to detect low-level actions and events. Used sensors include RFID readers, magnetic sensors, temperature sensors, pressure and presence sensors. We have acquired a dataset of IADLs and anomalies related to medicine intake, meal preparation, and meal consumption, asking to voluntary actors to reproduce the daily routine of 21 patients in our smart home lab. Executed IADLs and anomalies realistically reproduce the behavior of two groups of elderly

persons: 7 healthy seniors (group 1), and 14 elderly people with early symptoms of MCI (group 2). We assumed that every individual lives alone in his/her home. We have considered seven categories of critical anomalies and four categories of non-critical ones. During his/her one-day routine, each individual in group 1 does not execute any critical anomaly, but may execute a few non-critical ones. Group 2 individuals may perform several non-critical and critical anomalies.

During the execution of the activities and anomalies, we have acquired the timestamped data coming from the sensors deployed in the smart home and we have manually annotated the dataset with the start- and end-time of activities and anomalies. Group 1 individuals did 7 non-critical and 0 critical anomalies; group 2 individuals did 29 non-critical and 28 critical anomalies. We experimentally evaluated the FABER method using *leave-one-day-out* cross-validation.

TABLE II  
PRECISION, RECALL AND F1 SCORE

ANOMALY TYPE	PRECISION	RECALL	F1 SCORE
Non-critical	0.893	0.926	0.909
Critical	0.923	1	0.96
TOTAL	0.898	0.964	0.93

Table II reports the results in terms of precision, recall and F1 score; the latter is the harmonic mean of precision and recall. The achieved precision was close to 0.9. Most false positives were due to mispredictions of the activity boundary detection module. However, the precision of critical anomaly recognition is significantly higher than the one of non-critical one. When activity boundaries were correctly recognized, in most cases FABER recognized the occurred anomalies, achieving an overall recall larger than 0.96. Overall, the system produced 6 false positives during the 21-days activities of the two groups. We claim that the number of false positives is compliant with the requirements of clinicians, especially considering that the individuals totally performed more than 150 instances of activities during the experimentation. A preliminary clinicians' assessment of the FABER system can be found in [15].

## V. CONCLUSIONS AND FUTURE WORK

In this paper we addressed the challenging issue of unobtrusively recognizing abnormal behaviors exhibited by elderly persons at home. We have proposed the FABER hybrid technique to recognize anomalies at a fine-grained level, based on the integration of supervised learning and symbolical reasoning, and on sensor data acquired from the smart-home infrastructure. Differently from existing approaches, our method provides detailed information about the detected anomalies, which can be exploited by practitioners for early detection of MCI. We designed the models of anomalies collaborating with cognitive neuroscience experts, and we implemented a prototype of FABER in a smart home lab. Experiments with a large dataset of activities show that FABER achieves high recall while generating a small number of false positives.

The achieved results are promising, but we plan to improve this work in several directions. Our current anomaly recognition method is based on non-probabilistic rules that strictly determine the detection of an abnormal behavior based on a user-defined set of observations. We consider extending this rigid system with probabilistic reasoning, possibly by means of a probabilistic logic. We also plan to investigate alternative activity recognition methods to improve the activity boundary detection rates. Other future work includes addressing the case of multi-inhabitants, concurrent and interleaved activities. Finally, we are working closely with clinicians to extend the set of significant anomalies to be monitored and we are already conducting experiments in patients' homes.

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