Analysis of Long-term Abnormal Behaviors for Early Detection of Cognitive Decline

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***Abstract*—Several researchers have proposed methods and designed systems for the automatic recognition of activities and abnormal behaviors with the goal of early detecting cognitive impairment. In this paper, we propose LOTAR, a hybrid behavioral analysis system coupling state of the art machine learning techniques with knowledge-based and data mining methods. Medical models designed in collaboration with cognitive neuroscience researchers guide the recognition of short- and long-term abnormal behaviors. In particular, we focus on historical behavior analysis for long-term anomaly detection, which is the principal novelty with respect to our previous works. We present preliminary results obtained by evaluating the method on a dataset acquired during three months of experimentation in a real patient's home. Results indicate the potential utility of the system for long-term monitoring of cognitive health.**

I. Introduction

Ubiquitous computing technologies have a recognized potential in supporting independent living and pro-active healthcare. These application areas are becoming strategic for many international research programmes considering that the senior population (aged over 65) is projected to double as a percentage over the whole population in the next decades [1]. Among the most frequent threats to independent living is cognitive decline, whose early symptoms often lead to a Mild Cognitive Impairment (MCI) diagnosis. According to 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 [2]. Hence, monitoring of daily living activities and recognition of abnormal behaviors may help practitioners to early detect the onset of cognitive impairment.

Several research projects, and numerous research papers have tried to detect behavioral markers of MCI onset through ubiquitous computing technologies, obtaining a correlation between the predicted and actual cognitive status of the patient. Some of these approaches require the execution of ability tests about the performance of IADLs in an instrumented smart home of a hospital [3]; hence, they incur in high costs and cannot be applied on a long-term basis. Some of them deploy cameras and sensor networks in controlled environments and use video and audio for activity recognition [4]: they are often perceived as too invasive for the individual's privacy. Other works rely on continuous monitoring of low-level behavioral markers (steps taken, walking speed, ...) and trigger alarms for anomalies whenever they detect situations sufficiently distant from the expected (modeled) behavior [5]: they provide little support to the diagnosis, since they do not report fine-grained descriptions of the anomalies occurred during the execution of IADLs.

In most of the above mentioned works, the detection of abnormal behaviors is done on a short-term basis. Other works derive a model of the patient's usual behavior from the activities performed in the past and use this model to detect anomalies as changes from the usual behavior. In [6], a method has been proposed to monitor the circadian (24-hours) variability of the patient's activities using location sensors and statistical analysis. In [7] in-home activities and sleep restlessness were captured using different sensors; changes in the activity patterns generate health alerts that were sent to clinicians to be rated for their clinical relevance and used as ground truth for developing classifiers to recognize relevant alerts. In [8], frequently-occurring temporal relationships between activities were extracted from the observed history of sensor events and used to model the probability that a particular event should or should not occur on a given day. All these works, however, still consider anomaly detection as the recognition of a short-term activity pattern as abnormal. What we propose in this work, instead, is a long-term analysis to detect significant changes in the trend of performing activities and to avoid raising alerts for isolated abnormal activities.

In this paper we report our latest results from a research project aimed to support early detection of mild cognitive impairment (MCI) for elderly people living independently at home. We propose a framework called LOTAR characterized by the following features: a) it heavily relies on indicator models built by cognitive neuroscience experts, b) it continuously acquire data from non-intrusive sensors deployed in the patient's home, c) it features an effective hybrid abnormal behavior recognition technique coupling state-of-the-art machine learning with knowledge-based inferencing, d) it provides clinicians with a dashboard identifying fine-grained short-term abnormal behaviors (e.g., inappropriate timing in assuming food or medicine intake, improper use of equipment, unnecessary repetitions of actions), but more importantly showing automatically recognized long-term abnormal behaviors (e.g., changes in habits regarding timing of meal consumption).

The rest of the paper is structured as follows. Section II presents the model of activities and anomalies. Section III illustrates the framework and the algorithms for abnormal behavior recognition. Section IV reports experimental results. Finally, Section V concludes the paper.

II. Modeling activities and abnormal behaviors

In the following we explain how we model human activities, short-, and long-term abnormal behaviors.

A. Human activities

We model human activities adopting the framework described in [9]. In particular, we use an extension of the OWL 2 [10] ontology presented in that work.[1] Each IADL consists of a sequence of simple actions. For instance, a patient could perform the IADL "taking medicines" by executing this sequence of actions: open the medicine repository, retrieve the medicine box, return the medicine box, and close the medicine repository. The same activity can be performed by executing different sequences of actions. Since we focus on IADLs, we assume that each action corresponds to a manipulative gesture or other body movement involving an object (e.g., "open the silverware drawer", "sit on the kitchen chair').

B. Short-term abnormal behaviors

By *short-term abnormal behaviors* we define those behaviors observed within a relatively short time period (from a few seconds to a day) that diverge from the expected ones, according to a given model provided by clinicians. In this work we concentrate on anomalies that may indicate the onset of MCI. We adopt the categorization of behavioral anomalies proposed in [11]:

- *omissions*: when an action or a sequence of actions composing an IADL is not performed (e.g.; "the elderly forgets to consume a meal after having prepared it");
- *commissions*: when actions within an activity are performed inaccurately (e.g.; "putting butter in a non-refrigerated storage");
- *additions*: when actions unnecessary to complete the current activity are performed (e.g.; "the elderly retrieves a food item not needed for lunch preparation").

In order to identify a set of significant anomalies to be considered in our experimental evaluation, we collaborated with cognitive neuroscience experts from the Institute Fatebenefratelli[2], Lombardy –a leading center in the field of mental health research and research on neurodegenerative disorders– within the SECURE[3] research project funded by Lombardy region and MIUR Italian ministry. The considered anomalies are related to food preparation and consumption, and adherence to the medical prescriptions, covering the whole spectrum of the anomaly classification presented above.

[1] http://webmind.di.unimi.it/care/smartfaber.owl

[2] IRCCS (Research and Care Institute) St John of God Clinical Research Centre, Brescia – http://www.irccs-fatebenefratelli.it

[3] SECURE: Intelligent System for Early Diagnosis and Follow-up at Home, http://secure.ewlab.di.unimi.it/

C. Long-term abnormal behaviors

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 impairment. Consider, for instance, the anomaly of leaving repositories open. This may be normally done by cognitively healthy people for negligence or hastiness. Hence, when considered in isolation, short-term abnormal behaviors are only weak indicators of possible cognitive issues. On the contrary, the frequency of anomalies detected over long periods of time and their temporal trend are much stronger indicators.

We define as *long-term abnormal behaviors* those groups of activities and anomalies, observed over relatively long periods of time (from one week to several months), showing significant changes from the normal trend observed in the past, and which may indicate the onset of cognitive impairment or the progression of MCI. Long-term abnormal behaviors are better indicators when *personalized*, i.e., when specified with respect to trends observed as 'normal' for a specific patient or patient-profile. In this paper we focus on abnormal behaviors that emerge from a personalized long-term temporal analysis of performed activities (e.g., considering time of meal consumption, duration of meal preparation), since time-related difficulties in task executions are known to be associated with MCI onset [12].

III. Recognizing long-term abnormal behaviors

In this section, we illustrate the *LOng-Term Abnormal behavior Recognition* (LOTAR) recognition framework.

A. Recognition framework

In Figure 1 we show the general architecture of LOTAR. Its core is composed of two main software modules: (i) the SmartFABER algorithm takes as input the timestamped sensor data and the models of abnormal behaviors, and it returns recognized actions, activities and short-term anomalies; (ii) the historical behavior analysis module performs historical data analysis on the output of SmartFABER to identify long-term abnormal behaviors. The outputs of both short- and long-term abnormal behavior recognition are transmitted to the e-HealthCare service, and can be inspected by clinicians through a Web dashboard.

B. Sensor data acquisition and semantic integration

The sensing infrastructure consists in an unobtrusive sensor network, which monitors the interaction of the elderly with the home environment by combining different sensing devices like environmental sensors, magnetic sensors, presence sensors and RFID tags. A software layer is in charge of collecting the data from the sensor network, and performing a semantic integration of raw detections to recognize the individual's actions. In particular, we adopt propositional logic rules to express conditions about the type of detected raw events, which determine the recognition of high-level actions. Those rules may include conditions about the temporal occurrence

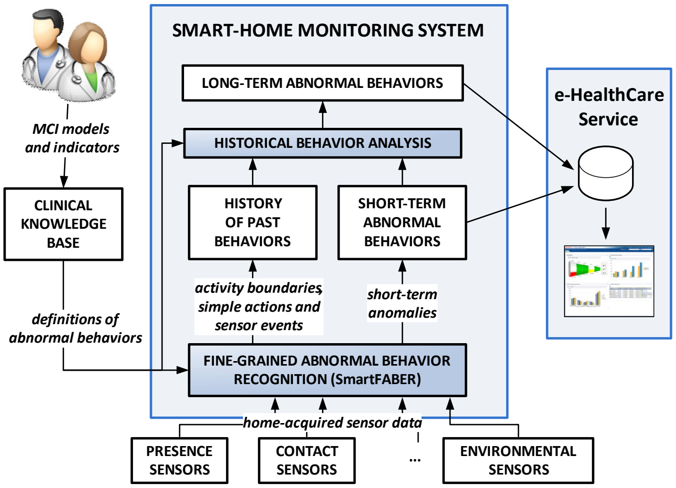


Fig. 1. The LOTAR framework to recognize long-term abnormal behaviors

of raw sensor events. An example is the detection of action *sitting on a chair at the kitchen table* as a temporal condition between raw sensor events revealed by a presence sensor over the table and a pressure sensor under the chair.

The system assigns a unique timestamp to each recognized action, based on the timestamps of the corresponding sensor events. For the sake of interoperability, event types and actions are represented using our OWL 2 SmartFABER ontology.

C. The SmartFABER algorithm

The SmartFABER algorithm includes both statistical techniques and knowledge-based reasoning. In the following we briefly describe its main components.

1) Recognizing activity instances: The input of SmartFABER's activity recognition algorithm is the sequence of recognized timestamped actions. A time-based feature extraction algorithm is in charge of building, for each action, a feature vector that represents the sequence of the n most recent actions. We adopted the feature extraction technique proposed in [13], since it considers temporal relations between actions and proved to be effective for recognizing complex IADLs given a temporal sequence of sensor events. A multi-class classifier (previously trained using a training set of activities and corresponding actions) is used to predict for each feature vector the most probable performed activity. Then, a post-processing algorithm exploiting temporal and semantic reasoning is in charge of grouping together all those classified actions that more likely belong to the same activity instance; the first (resp. last) action of an activity instance determines the start- (resp. end-)time of that instance. The activity recognition technique is presented in detail in [14].

2) Anomaly detection: Inferred activity boundaries are communicated –together with recognized actions– to a knowledge-based inference engine to detect short-term anomalies. Our anomaly recognition technique is extensively discussed in [14]. Essentially, natural language descriptions of anomalies provided by clinicians are translated in propositional logic rules and added to the knowledge base. Moreover, we use our OWL 2 ontology, including a taxonomy of food items, objects, and furniture, to instantiate context dependent facts in the knowledge base. In particular, food items are classified in those that must be refrigerated, and those that must not. Similarly, cabinets are classified in refrigerated and non-refrigerated ones. For each instance of food item, object, and furniture in the ontology, a corresponding fact is automatically added to the knowledge base. The knowledge base also contains axioms about medical prescriptions for medicine intake.

At the end of each day, the inference engine evaluates the rule-based anomaly definitions considering the inferred activity instances and actions and the context dependent facts. Each detected anomaly is represented by the category of the anomaly, the object (or activity) involved in that anomaly, and the time instant at which the anomaly has happened.

D. Historical behavior analysis

While what we call short-term anomalies in this paper identify situations that can be precisely specified and effectively detected through symbolic methods, long-term abnormal behaviors are characterized by wide inter- and intra-individual variability; hence, we rely on a personalized statistical approach to detect them. In our approach, we map the daily activities of the patient in *activity feature vectors*, which succinctly describe some characteristics of interest of the activities performed during a given period (e.g., one day). The goal is to statistically monitor the temporal evolution of those vectors to detect significant changes from the patient's usual behavioral pattern.

1) Building activity feature vectors: Of course, the technique to build activity feature vectors depends on the considered activities, on their characteristics of interest and on the patient's profile. In the following, we illustrate an application of the technique considering meal preparation activities, where the characteristics of interest is the temporal distribution of their occurrences during the day.

Example 1: In order to represent the distribution of meal preparation activities during a day, we partition the day in k time slots, not necessarily of equal length, and map each occurrence of meal preparation to the time slot in which that activity has ended. Hence, for each day we build an activity feature vector v_i of length k that stores the number of meals prepared during each time slot during day i. For example, if we consider the partition:

0: breakfast	5am - 11am
1: morning	11am - 12noon
2: lunch	12noon - 3pm
3: afternoon	3pm - 6pm
4: dinner	6pm - 10pm
5: night	10pm - 5am

vector $v_i = \langle 102010 \rangle$ means that "during day i, the patient prepared one meal within the breakfast slot, two meals within the lunch slot, and one meal within the dinner slot; he/she did not prepare any other meal during that day".

2) Mining for long-term abnormal behaviors: In order to detect whether there has been any recent change in the patient's habits, we compare the activity feature vectors of the last n days (called *current period*) with the ones observed in a preceding period of m days (called *baseline period*), with $m \gg n$. Note that there is no intersection between the days in the baseline period and the ones in the current period. We assume that the baseline period represents the usual behavior of the patient in a recent past. A frequent pattern mining [15] algorithm can be applied to the activity feature vectors of the baseline period B to obtain the set V of typical activity routines; i.e., those vectors whose frequency in B is equal to or larger than the support value s. Then, for each day i in the current period C, we check whether the associated vector v_i appears in V or not. If not, we consider day i as *anomalous*. If the rate of anomalous days during C exceeds the threshold t, we detect a long-term anomaly during C and the algorithm returns the set of anomalous days in C.

The algorithm pseudo-code for checking if a long-term abnormal behavior occurred in the current period is shown in Algorithm 1. Note that F is the set of frequent patterns, while N is the set of anomalous days. The function set takes as input a sequence and outputs the set of its elements (without repetitions). The algorithm is executed using a sliding window approach: for instance, each day it is executed considering the last two weeks as the current period, and the previous three months (last two weeks excluded) as the baseline period.

Input:
C: set of days of the current period; B: set of days of the baseline period; s: minimum support value for frequent pattern mining; t: threshold for anomalous days in C; S_C, S_B sequences of activities feature vectors associated to the days in C and B, respectively.

$F \leftarrow \emptyset$; $N \leftarrow \emptyset$; $S'_B \leftarrow set(S_B)$
forall $w \in S'_B$ **do**
  if w *appears in* S_B *at least* s *times* **then** $F \leftarrow F \bigcup \{w\}$
end
forall $v_i \in S_C$ **do**
  if $v_i \notin F$ **then** $N \leftarrow N \bigcup \{i\}$
end
if $|N| \geq t \cdot |S_C|$ **then**
  return N
else **return** $\emptyset$

Algorithm 1: Long-term abnormal behavior detection

3) Extensions to consider periodic routines: Based on the individual's profile, the mining algorithm can be refined to take into account periodic habits and routines. For instance, it is possible to divide the days used for the analysis into classes (e.g., working days vs holidays), and apply the algorithm to each class separately to discover changes in periodic routines or abnormal behaviors correlated with them.

4) Profile-based calibration of parameters: Parameters s and t need to be carefully calibrated based on the patient's habits. In general, increasing the value of s reduces the number of activity feature vectors that are considered normal, and therefore increases the number of days in the current period detected as anomalous. A higher value of t, instead, will make the algorithm require a higher portion of abnormal days to output a long-term anomaly. To effectively run the analysis, we need to carefully balance those values, so that we can properly recognize whether the current days are deviating from the baseline activity pattern.

In the following we explain our approach to calibrate s and t values. We fix the value s based on the profile of the patient. If the patient has very regular habits, he/she would tend to execute very frequently a limited set of routines. In this case, a relatively high value of s should be chosen, to include only his/her normal routines in the set of frequent activity feature vectors. On the contrary, a relatively low value of s should be chosen when the patient has not very regular routines, to account for the wide variability of his/her typical activity patterns. The patient's profiling can be done manually by practitioners during the clinical assessment, or by automatically mining a dataset of the typical activity routines of the patient. The value of s should be periodically re-calibrated to account for changes in the patient's habits.

After fixing s, we initially set the value of t to a default value, which is currently manually chosen according to the current cognitive status of the patient. The value of t is periodically re-calibrated considering the clinical assessment of the patient.

IV. EXPERIMENTAL EVALUATION

We implemented a prototype of the LOTAR framework and we extensively evaluated it using a dataset acquired during three months of experimentation in the home of an elderly woman diagnosed with MCI. The IADLs that we selected to validate our method are: *taking the prescribed medicines*, *preparing a meal* and *eating a meal*.

A. Hardware and software implementation

The sensing infrastructure of LOTAR is composed of several kinds of sensors that unobtrusively capture the interaction between the subject and the home environment. Those sensors, which are deployed on various household items, are listed in Table I. The core software modules of LOTAR are implemented for the Android platform, since the system is intended to run on a mobile device located inside the subject's home. We also developed a Web dashboard, to

TABLE I
MONITORED HOUSEHOLD ITEMS

Monitored items	Related sensors
Medicines boxes, Food items containers	RFID readers
Medicines cabinet, Fridge, Non-refrigerated food cabinet, Cooking pan cabinet, Silverware drawer	Magnetic sensors
Stove	Temperature sensor
Kitchen table	Presence sensor
Kitchen chair	Pressure sensor

allow clinicians inspecting the trend of performed IADLs and abnormal behaviors.

B. Dataset

We deployed our framework inside the home of a real patient: an elderly woman aged 74, with early symptoms of MCI and medical co-morbidities, who lives alone. We acquired a dataset of 55 days of IADLs performed by the elderly. A detailed description of the smart home setup is reported in [16]. The set of considered short-term anomalies were provided by the clinicians, together with time prescriptions for meals and medicines assumptions. The clinicians divided the anomalies in three levels of seriousness: green (e.g.; if a meal is consumed out of the prescribed time), yellow (e.g.; if a meal is skipped), and red (e.g.; if a prescribed medicine is not taken). This classification is orthogonal to the one presented in Section II. Totally, we collected 181 instances of activities and 605 short-term anomalies (most of them green and yellow ones).

Due to privacy issues, it was not feasible to annotate activities and anomalies by directly observing the elderly during the execution of the activities, except for a limited amount of time (mainly during the system setup). The activities were labeled offline by manually analyzing the collected raw sensor detections; the IADLs that we considered in this work are relatively easily discriminable by a human observer. The anomalies were automatically annotated by running the corresponding definitions over the collected sensor events, actions and labeled activities.

C. Activities and short-term anomalies

In order to assess the effectiveness of activity boundaries and short-term anomaly recognition, we performed an extensive evaluation of the SmartFABER method. In order to obtain meaningful measures of the prediction's quality, we performed leave-one-day-out cross-validation estimating the standard measures of precision, recall and F_1.

For the activity boundary detection task, we obtained a F_1 score slightly above 0.8, with a good balance of precision and recall. The performance of our algorithm was negatively affected by noisy sensor measurements (that consist in missing or incorrect readings), as well as by the wide variability of IADLs execution patterns of the subject. However, success rates can improve by considering a larger training set of activities, and introducing redundancy in the sensor infrastructure.

Of course, anomaly recognition rates depend on the accuracy of the activity recognition method. Indeed, fluctuations in the error rate for different activities may have differently amplified effects on the recognition of anomalies. Moreover, there are anomalies that are based on presence or absence of single actions, not activities. Hence, it is important to evaluate the accuracy of anomaly recognition against annotated data. For the anomaly recognition task, we achieved a F_1 score of 0.785, obtaining a good balance between precision (0.76) and recall (0.81).

D. Long-term abnormal behavior recognition

We have applied the technique to recognize long-term abnormal behaviors (Algorithm 1) using the patient's dataset and the meal preparation routines discussed in Section III-D. We have used the time slots shown in Example 1, which were calibrated according to the patient's habits. We have considered a baseline period (B in Algorithm 1) of 30 days from 30 October 2014 to 22 December 2014. We had to skip some days due to temporary failures of the sensor platform used for the data acquisition. For the sake of simplicity, we have considered the days in the test period as consecutive, disregarding skipped days. We have applied our algorithm, with a temporal sliding window of 7 days (C in Algorithm 1), over a test period ranging from 10 January 2015 to 15 February 2015, for a total of 32 days. We have used our profile-based technique for parameter calibration. According to the patient's clinical profile, we have set $s = 2$ and $t = 0.5$. As explained in Section III-D, s must be carefully calibrated according to the personal profile and health status of the subject. In our case, we have chosen a small value for the support s, since the subject exhibited large variability in the execution pattern of activities, probably due to MCI symptoms. The value t ($0 \leq t \leq 1$) determines the sensibility of the long-term recognition algorithm: in our experimentation we have chosen an intermediate value.

The algorithm detected two long term anomalies, one from 12 January to 23 January, and one from 29 January to 6 February. Those intervals are shown in Figure 2 as horizontal bars. The days that were classified as anomalous by the algorithm are colored in violet. According to the choice of parameters, each abnormal interval bar includes at least 4 anomalous days. In order to understand whether those intervals actually correspond to a period characterized by anomalous behaviors, we have identified the days in the overall test period in which the highest number of red anomalies occurred. We found 5 days in which the patient did 7 or more such anomalies (identified by a red square in the figure), while in the other days no more than 5 red anomalies occurred. We can notice that 4 out of 5 among those days are contained in the two intervals. We believe that the correlation is significant, especially considering that our long-term abnormal behavior recognition algorithm considered meal preparation activities, while red anomalies regard medicine intake, which are not related to meal consumption according to the patient's clinical prescriptions. However, we point out that more extensive experiments, carried out with more patients and for longer time periods, are needed to thoroughly assess the effectiveness of the algorithm.

We also computed the long-term trend of the occurrences of short-term abnormal behaviors, using a simple sliding window approach: for each day in the dataset, we count the number of anomalies detected in the 15 previous days. Figure 3 shows a comparison between the results obtained using the LOTAR technique and the actual ones (i.e., the ground truth). We can notice that, in general, the amount of anomalies detected with

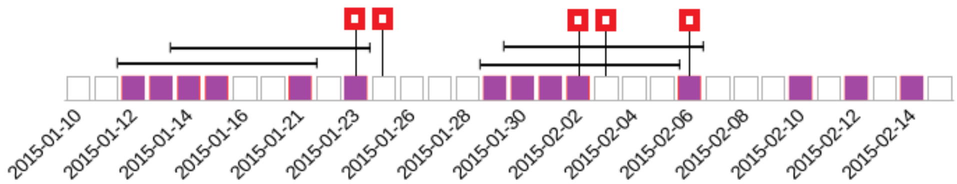
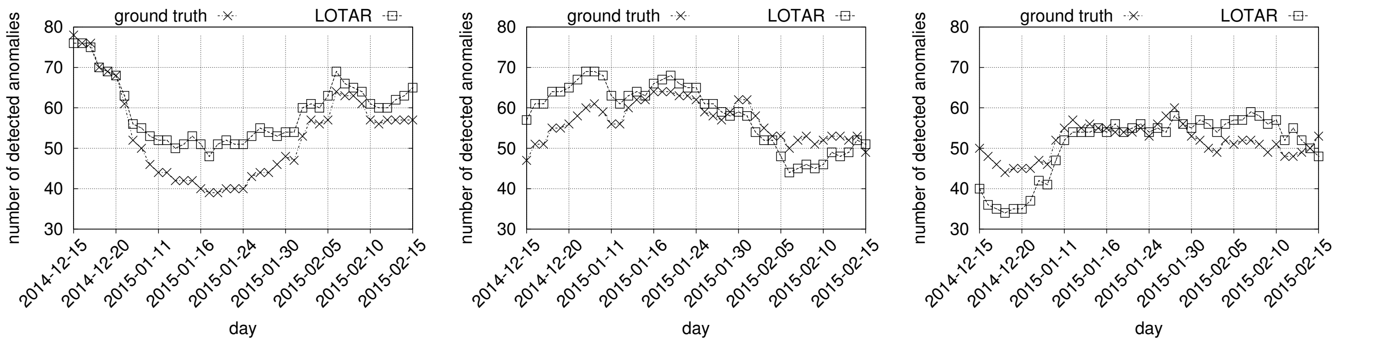


Fig. 2. Detection of two long-term abnormal behavior intervals with LOTAR



(a) Red anomalies (b) Yellow anomalies (c) Green anomalies

Fig. 3. Trend of short-term abnormal behaviors. For each day, the value represents the number of anomalies detected in the previous 15 days.

our technique is close to the ground truth. Moreover, we can notice that, despite the differences in value, the general trend is preserved; hence, LOTAR provides the clinicians with a reliable tool to recognize significant changes in the rate of anomalies.

V. Conclusions and Future Work

In this paper we have extended our previous work on the recognition of abnormal behaviors in performing daily activities with methods for detecting long-term deviations from what can be considered normality for a specific individual. While first experimental results seem to validate the effectiveness of the technique, many aspects deserve further investigation including modeling different kinds of long-term anomalies, considering alternative mining algorithms, and extending the experiments to multiple individuals.

Acknowledgments

The authors wish to thank Laura Musica for her contribution in carrying out the experimental evaluation. This work was partially supported by the project "SECURE: Intelligent System for Early Diagnosis and Follow-up at Home", funded by a grant of Lombardy Region and Italian Ministry of Education, University and Research.

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