Behavioral Monitoring in Smart-Home Environments for Health-Care Applications

Gabriele Civitarese

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

Email: gabriele.civitarese@unimi.it

I. INTRODUCTION

It is projected that over 20% of the world population will be aged over 60 in 2050. Of course, aging increases the risk of incurring in cognitive disorders like Mild Cognitive Impairment or Dementia. This will a have huge impact, first of all, on the ability of independent living and on the quality of life for those fragile subjects. Moreover, the sustainability of health-care systems would be compromised, both for higher costs and the lack of sufficient available medical staff to assist those individuals. In the literature, many pervasive solutions have been adopted to continuously and unobtrusively monitor the behavior of fragile subjects directly in their homes. Those systems have the objective of preventing, curing, and improving wellness and health conditions of those individuals. Using unobtrusive sensors deployed in the home environment avoids the privacy issues of video/audio based solutions (unacceptable for many subjects in home environments) and the obtrusiveness of wearable solutions. Reasoning algorithms are in charge of detecting what the subject is doing (e.g., activities carried out) and possible abnormal behaviors. The produced information is of great value for clinicians, providing them indicators for early diagnosis of health diseases (e.g., cognitive impairment). In this paper I summarized a set of contributions in this field as part of my PhD thesis.

II. CHALLENGES AND STATE OF THE ART

Unobtrusively monitoring the behavior of fragile subjects in their homes poses several issues. Raw sensor data need to be analyzed in order to infer what people are doing and the behavior abnormalities. The first important step is to infer which Activities of Daily Living (ADLs) are carried out. In fact, clinicians are interested in those subtle differences in performing ADLs which can be symptoms of cognitive decline. Several activity recognition solutions have been proposed in the literature in the last years. Many of them are based on supervised methods, which exploits statistical techniques to infer the performed activities [1]. The main drawback of these approaches is that they require a large annotated dataset, which is often unfeasible to acquire. Even if those datasets exist, they may be tight to specific subjects/environments, thus lacking the capability of generalization. On the other hand, several works proposed symbolical methods, mainly based on logical formalisms used to define the semantic of ADLs [2]. The advantage of those methods is that they capture complex relations between sensor events which strongly characterize activities. The main drawbacks are the inflexibility (it is difficult to capture all the possible ways of performing ADLs) and the inability of dealing with the intrinsic uncertainty of sensor readings. Hybrid methods which combine statistical and symbolical reasoning have been proposed to take advantage of the strength points of the two approaches while avoiding the weak points [3]. The detection of abnormal behaviors (i.e., deviations from "regular" ways of performing activities as significant markers for medical diagnosis) is a more recent research field. The general approach is to build a model of the "regular" behavior in order to identify those ADLs patterns which diverge from the expected ones [4]. The main issue of those methods is that all behavioral changes are detected without giving specific explanations. Other research groups adopted supervised methods to refine the identification by recognizing the general anomaly's category (e.g., omission, substitution, replacement, . . .) [5]. However, the results show an high rate of false positives.

III. NOVEL CONTRIBUTIONS

The contribution of our work is to design and experiment new methods to unobtrusively monitor the inhabitant of a smart-home, capturing the occurred fine-grained abnormal behaviors. The detection of those anomalies allows to support the clinical diagnosis of cognitive diseases; hence their models should be defined by experts in neuropsychology. It is important to note that the occurrences of those anomalies are not intended to provide an automatic subject's cognitive assessment. However, their frequencies and temporal trend can be used to derive behavioral changes. Differently from the other solutions, the occurred abnormal behaviors are inferred at a very fine granularity (e.g., "the subject is eating more cold meals than the usual", "the subject retrieved a prescribed medicine from the repository but then forgot to take it", . . .). A preliminary version of this system has been achieved in [6], obtaining promising results.

Our specific contributions can be summarized as: a) the design of new supervised and unsupervised hybrid ADLs recognition algorithms which also deals with interleaved activities, b) the design of a fine-grained anomaly recognition framework capable to obtain a low number of false positives.

IV. METHODOLOGY

Choosing a robust and reliable sensing infrastructure is a key factor to obtain a more reliable recognition. Due to the fine

granularity of ADLs and anomalies that we are interested in monitoring, the choice of the specific sensors to use is crucial and it is evaluated in the details. In our experience, Z-Wave based environmental sensors (e.g., magnetic, power, presence and pressure sensors) are a good choice to unobtrusively and reliably monitor the interaction of the subject with the home environment. Moreover, we exploited tiny BLE accelerometers placed on everyday objects (e.g., medicine boxes, food packages, cutlery, . . .) to monitor the performed manipulations [7]. Environmental sensors data are pre-processed in order to be translated into high-level events using simple inference rules (e.g., if the pressure sensor on a kitchen chair fires that someone is sitting and in the meanwhile the presence sensor indicates that someone is at the dining table, the event "sitting at the dining table" is inferred). Instead, accelerometer data produced by the monitored objects are analyzed by a machine learning module which infers the performed manipulations (e.g., the bottle has been used to pour water). As previously mentioned, abnormal behaviors recognition is highly dependent on the detection of performed ADLs. Regarding the recognition of ADLs, we designed two different hybrid solutions both capable of capturing interleaved situations. In [6] we exploited a combination of supervised learning and semantic/temporal reasoning to infer the performed activities. Combining statistical and symbolical reasoning allowed us to consider the intrinsic uncertainty of sensor measurements while capturing complex semantic relations which can not be considered by purely statistical methods. The main drawback of this approach is that it requires a large annotated dataset. For this reason, we also proposed an unsupervised solution [8] which combines ontological and probabilistic reasoning. Essentially, an ontology is used to compute the correlations between home instruments/furnitures and ADLs. Using those correlations, a probabilistic logic is in charge of computing the most probable activities performed by the subject. Of course, the drawback of this solution is the effort needed in designing the ontology. Finally, the anomaly recognition module analyzes pre-processed sensors data and detected ADLs in order to infer the occurred fine-grained anomalies. In [6] we proposed a symbolic approach, using first-order logic rules to formalize the model of abnormal behaviors provided by clinicians. Those rules involves temporal and semantic relations between environmental sensor events, objects manipulations, performed ADLs and specific information about the monitored subject and its environment.

V. EVALUATION

All the proposed methods have been extensively evaluated. We acquired several annotated datasets: one dataset acquired during a three-months deployment in a real-home of a MCI subject and two datasets acquired in two different smart labs. Those datasets comprised several instances of ADLs (even executed in an interleaved fashion) and anomalies.

The evaluation of ADLs recognition algorithms showed their effectiveness on the considered datasets. The supervised approach proposed in [6] performed better in the smart lab scenarios (with an overall F_1 greater than 0.9), while it was less accurate in the real home (with an overall F_1 slightly above 0.8). This is due to a more noisy and faulty sensing infrastructure in the real environment. Moreover, the unsupervised algorithm proposed in [8] proved to be comparable with the supervised approach, with the great advantage of not requiring an annotated dataset. Finally, the results on anomaly recognition proved to be as well satisfactory. The overall F_1 value obtained is around 0.9, with a very small number of false positives (mainly due to malfunctioning in sensing devices). The obtained results are very promising: the considered dataset consisted in more that 700 activity instances, while only 150 of them included abnormal behaviors. Hence, rarely an ADL executed in a "regular" way was fired as anomalous (the true negative rate is very high).

VI. CONCLUSIONS

Although the method discussed in this work already obtained promising results, we plan to extend it in several directions. First of all, anomaly recognition relies on a too rigid formalisms which is not able to capture the intrinsic noise of sensor measurements. Moreover, semi-supervised ADLs recognition techniques (e.g., active learning) will be evaluated in order to better adapt the model to different users and environments. Last but not least, we aim to improve our algorithms in order to support parallel activities and multi-inhabitants scenarios.

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