Proposed Human Activity Monitoring In Smart – Home Environment

[1]ADEDARA, Raphael Oluwadare & [2]AJISOLA, Kolawole Thomas & [3]AWODUN, Mojirade Adejumoke
[1,2]Computer Science Department, College of Education, Ikere-Ekiti, Ekiti State, Nigeria

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ABSTRACT: *Effective chronic disease management ensures better treatment and reduces medical costs. With a growing population of elderly people, the number of subjects at risk of cognitive disorders is rapidly increasing. Many research groups are studying pervasive solutions to continuously and unobtrusively monitor fragile subjects in their homes, reducing health-care costs and supporting the medical diagnosis. Clinicians are interested in monitoring several behavioral aspects for a wide variety of applications: early diagnosis, emergency monitoring, assessment of cognitive disorders etc. Among the several behavioral aspects of interest, anomalous behaviors while performing activities of daily living (ADLs) are of great importance. Indeed, these anomalies can be indicators of serious cognitive diseases like chronic diseases. The recognition of such abnormal behaviors relies on robust and accurate ADLs recognition systems. Moreover, in order to enable unobtrusive and privacy-aware monitoring, environmental sensors in charge of unobtrusively capturing the interaction of the subject with the home infrastructure should be preferred. This paper presents several contributions on this topic, the ADLs recognition algorithms used are: data-driven, knowledge-driven, and hybrid. The former are supervised while the latter is unsupervised. Preliminary results, which still need to be confirmed, show that the recognition rate of the unsupervised method is comparable to the one obtained by the supervised one, with the great advantage of not requiring the acquisition of an annotated dataset. Beyond ADLs recognition, other contributions on smart sensing and anomaly recognition are presented. Regarding unobtrusive sensing, we propose a machine learning technique to detect fine-grained manipulations performed by the inhabitant on household objects instrumented with tiny accelerometer sensors.*

Key Words: *human activity, monitoring, smart, smart-home, environment*

1. Introduction

The new sensing applications need enhanced computing capabilities to handle the requirements of complex and huge data processing. The new era of Knowledge Society has brought advanced services for improving the quality of life of citizens and making better use of resources. These services are based on modern paradigms of Information and Communication Technologies (ICT) such as the Internet of Things (IoT) and the Cloud Computing paradigms. In this way, new concepts have been created which apply IoT to benefit different areas of society and industry. For instance: ambient assisted living [54], smart cities [53]. In these scenarios, new data management issues arise for integrating environmental sensor data efficiently and handling data from different sources [53].

Recent applications have been developed around the aforementioned concepts where sensing and processing capabilities of the devices play an important role. These devices are usually embedded systems and/or mobile devices such as smart phones, wearables, laptops, tablet PCs, etc.

Background to the study

Thanks to recent advances in medicine and to improved quality of life, life expectancy considerably increased thus allowing people to live longer and healthier with respect to previous generations. However, in an aging world population, more citizens are exposed to many challenges due to cognitive decline, chronic age-related diseases, limitations in physical activities and so on. This scenario brings negative consequences on the ability of independent living and the quality of life of these fragile subjects, but also on the sustainability of healthcare systems [1].

The majority of patients prefer to stay in the comfort of their own homes, and given the costs of nursing home care [2], it is imperative to develop technologies that help older adults to age in place. For these reasons, independent living and pro-active health-care are becoming strategic application areas for major research programmes all over the world [3], considering that the senior population is projected to double as a percentage over the whole population in the year 2030 [4].

Indeed, many research groups are studying pervasive solutions to continuously and unobtrusively monitor fragile subjects at their homes, reducing health-care costs and supporting the medical diagnosis. These studies are possible due to the increased availability of affordable and reliable sensing infrastructures, which allowed to build the so-called smart-homes: residences equipped with technology (i.e. sensors and actuators) that enhances the safety of patients at home and monitors their health conditions [5]. Continuous in-home monitoring should avoid video/audio recording, since it is often perceived as too privacy obtrusive in a home environment. Moreover, there are indications of a general adversity or disaffection of users to wearables sensors targeted to health-care related applications [6]. Hence, smart-home sensing infrastructures should mostly rely on environmental sensors in charge of capturing the interaction of the subject with the home infrastructure.

Among the several health conditions which can be continuously monitored within smart-homes, clinicians are interested in understanding the everyday functioning of individuals to gain insights about difficulties that affect the quality of life [7].

According to the International Working Group on choric diseases, there is evidence of subtle differences in performing activities of daily living (ADLs) among patients suffering from chronic diseases compared to both healthy older adults and individuals with chronic diseases [8].

One of the most frequent threats to independent living is chronic diseases. Hence, from a medical point of view, there is a clear interest in methods to monitor chronic diseases For these reasons, several pervasive frameworks to assess the behavior of smart-home's inhabitants have been proposed. Figure 1.1 illustrates the general architecture of such systems.

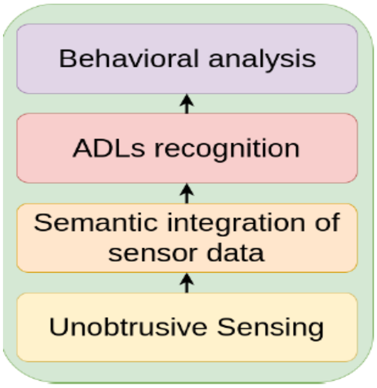

Figure 1: General architecture of behavioral analysis frameworks

The following are description for each component of this architecture:

1.1. Unobtrusive sensing

In order to recognize activities and anomalous behaviors, there is a need for a reliable and unobtrusive sensing infrastructure in charge of capturing the subject's interaction with the home environment [9]. Improvement of semiconductor fabrication technology and smart algorithms has made it possible to design and develop smart sensors with built-in intelligence [10]. For example, power sensors have been developed in order to monitor usage time and duration of different appliances. Also, water sensors exploit an in-line flow transducer to give an indication of when water is being used. Several wireless sensors have been used to monitor the execution of ADLs, like magnetic sensors, presence sensors, pressure sensors, power sensors, water sensors, etc.

A significant unobtrusive sensing system has been proposed in [11], where a smart apartment was equipped with a wide variety of sensing devices, like a smart floor to constantly measure gait and balance parameters of inhabitants, smart lighting, water monitoring, and many other sensors to continuously and unobtrusively monitor the subject's interaction with the home environment.

1.2. Semantic integration of sensor data

Raw sensor data by itself might not provide meaningful context that can be directly understood and utilized by behavioral reasoning algorithms. For example, if a sensor labeled as P3 attached to the electrical stove's plug detects a sudden increase of power consumption, we want to map it to the high-level concept "the kitchen's stove has been turned on". An abstraction layer is then needed to annotate sensor measurements with semantics that are structured around a set of contextual concepts [12] (e.g., smart-home infrastructure, household objects, home locations).

The advantage of mapping raw sensor data to semantic is that reasoning algorithms are independent from the specific sensing infrastructure being used. Hence, there is a need for tools that model at high-level the context gathered by raw sensor data. The survey proposed in [13] gives a broad overview of context modeling techniques in pervasive computing scenarios (e.g., Context Modeling Language [14], ontologies [15], hybrid methods [16]).

1.3. ADLs recognition

In order to accurately detect abnormal behaviors, a reliable ADLs recognition system is needed. Infact, detecting the specific activities being performed is sometimes a prerequisite to detect an anomaly [17]. An ADLs recognition algorithm takes as input the preprocessed sensor events and produces as output the most likely performed activities. The solutions are divided into two macro categories: data-driven and knowledge-driven.

(i) ***Data-driven methods***

Data-driven methods rely on machine learning techniques to build the activities' model from sensor data [18]. (i.e., training set of sensor data, labeled with executed activities). The strong point of this category of techniques is that they are good at handling the intrinsic noise and uncertainty of sensor data. The main flaw is that a large annotated dataset of ADLs should be acquired to capture most execution patterns in different situations [19]. Indeed, activity execution patterns are strongly coupled to the individual's characteristics and home environment, and the portability of activity datasets is an open issue [20]. As a result, ideally one extensive ADLs dataset should be acquired from each monitored individual. Unfortunately, acquiring ADLs datasets is very expensive in terms of annotation costs [21]. Besides, activity annotation by an external observer, by means of cameras or direct observation, violates the user's privacy.

Datadriven techniques are more flexible in terms of implementation (i.e., they do not require rigid definitions of activities) and they are more robust with respect to noisy and uncertain sensor data. Moreover, since they do not rely on a rigid specification of how ADLs should be performed, they potentially can capture more variations of the considered activities. For example, in case of the activity of preparing a meal, a person can turn on the stove in the beginning and then retrieve the food items from the cabinets or vice versa. Depending on the recipe, the person can skip or add some steps to the activity. Thus, in such cases we need techniques that are scalable. However, the acquisition of a comprehensive annotated dataset is expensive and often unfeasible. Moreover, it is difficult to incorporate the domain knowledge about the activity using these techniques.

Observations regarding the user's surrounding environment (in particular, objects' use), possibly coupled with body-worn sensor data, are the basis of those activity recognition systems [3, 32]. In [33] the authors propose a time series data analysis method to segment sequences of sensor events in order to recognize ADLs. The application of Hidden Markov Models inference is proposed in [34] to recognize activities based on features extracted from recent sensor events according to a sliding window. Conditional Random Fields [35] and Emerging Patterns [36] have also been proposed in order to detect sequential, interleaved and concurrent activities. The authors in [37] combine Bayes Networks with interval algebra in order to explicitly model complex temporal dependencies over time intervals. In [38], the authors propose a supervised learning classifier that automatically adapts its model according to the dynamically discovered context (i.e., new data sources). However, since training data is hard to acquire in realistic environments, systems relying on supervised learning are prone to serious scalability issues the more activities and the more context data are considered. Moreover, datasets of complex ADLs are strongly coupled to the environment in which they are acquired (i.e., the home environment and the sensors setup), and to the mode of execution of the specific individual. Hence, the portability of activity datasets in different environments is an open issue [39].

(ii) Knowledge-based methods

In order to solve these issues, knowledge-driven solutions have been proposed to manually specify ADLs through logic languages and ontologies. On the other hand, the knowledge-driven techniques are more powerful to represent the semantics of the sensor events. These techniques use the domain knowledge to conceptually model an activity. In this way, an activity can be modeled without the need for large training data. Those models are matched with acquired sensor data to recognize the activities [22]. The main advantage of these techniques with respect to data-driven methods is that they can capture complex semantic relationships between sensor events and activities.

The main shortcoming of this approach relies on the rigidity of specifications. For instance, complex ADLs are often specified through temporal sequences of simpler actions [23]. In fact, it is not always feasible to enumerate all the possible sequences of actions describing a complex ADL. Moreover, this rigidity does not allow to deal with noisy or uncertain sensor measurements.

However, such techniques lack the benefits of flexibility and scalability in the system. In addition to the above-mentioned methods, hybrid solutions have also been proposed to combine data-driven and knowledge-based approaches.

(iii) Hybrid methods

Given the limitations of both statistical and symbolic approaches, a few hybrid activity recognition systems have been discussed, which vary on the adopted reasoning techniques and on their interaction mechanisms.

An interesting instance of those approaches is Markov Logic Networks (MLN), a probabilistic first-order logic [40]. Given a training set, and a set of probabilistic formulas, with MLN it is possible to learn a weight for each grounded formula by iteratively optimizing a pseudo-likelihood measure. Those weights represent the confidence value of the formula. Deterministic formulas can be added to probabilistic ones to express deterministic knowledge about the domain of interest. Different reasoning tasks can be executed to infer additional information based on formulas and facts [19]. A similar approach was adopted in [23] to model and recognize activities at different levels of complexity using probabilistic description logic. The advantage of using probabilistic logic is that it allows defining complex knowledge-based constraints which can capture the intrinsic uncertainty of sensor measurements. Indeed, learning the weights of those constraints allows combining the strong point of knowledge-base and data-driven methods, thus improving the recognition rate. However, those approaches still require the acquisition of a labeled dataset. In [41] the authors proposed to exploit ontologies in order to derive semantic similarity between sensor events. This similarity is then used to segment sensor data, obtaining sequential activities' patterns used to train a clustering model. The semantic segmentation of sensor data allows to accurately individuate transitions between activities without supervised techniques. The main drawback of this method is that it requires a comprehensive dataset of activities (even if not labeled) acquired from the monitored subject to construct an accurate activities model.

Hybrid ontological and statistical reasoning is also proposed in [42] to continuously assess the fall risk of a senior at home, by integrating data acquired from different fall detection systems and environmental sensors. Semantic reasoning considering the context is hence used to reduce the number of false positives obtained by the statistical fall-detection system.

1.4. Behavioral analysis

Automatic and continuous monitoring of the behavior of fragile subjects addresses many issues of classic solutions. Indeed, questionnaires and interviews have been used to assess cognitive health about the ability to perform various kinds of ADLs [24]. This approach is of course prone to reporting bias; moreover, it cannot be applied for continuous monitoring, since it incurs evident overheads in terms of time, resources and monetary costs.

An anomaly detection system needs an accurate model of the regular behavior of the monitored subject in order to detect when anomalies occur. Indeed, different subjects may perform the same activities in very different ways. Moreover, each subject may adhere to his/her specific medical prescriptions (e.g., medicine intake time, diet, rehabilitation exercises etc). Time context (e.g., the day of the week, season, holidays etc) should also be taken into account, since activities can be performed differently depending on temporal context.

The majority of the proposed anomaly recognition methods exploit probabilistic [25] or clustering [26] techniques in order to construct the "normal behavior" of the subject analyzing sensor data without abnormal behaviors. Anomalies are then detected on new sequences of sensor data when divergences from the original model are found. The main drawback of this type of approaches is that behavioral changes are detected without giving specific explanations of what happened.

Some other works proposed supervised learning techniques to detect the general anomaly's category (e.g. omission, substitution, replacement etc) [27]. However, the results show a high rate of false positives. Moreover, the acquisition of a comprehensive annotated dataset of abnormal behaviors is hardly feasible.

Several European projects have addressed the usage of ICT technologies for enhancing active and healthy aging [43, 44, 45] and for supporting people with chronic diseases at home [46]. Based on this line of research, different works have proposed to apply machine learning techniques on data acquired in sensor-rich environments, for assessing the cognitive health status of an individual performing a set of ADLs. For instance, motion sensors and contact sensors have been used in [47] 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 chronic diseases subjects from healthy seniors.

A sensor-based infrastructure has been used in [48] to unobtrusively monitor the execution of ADLs by older adults in a smart-home; the results have shown a significant correlation between the cognitive health status of the subject and the level of assistance that he needs to complete the activities. In the work of

Dawadi et al. [49], 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, supervised 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 used to predict the health status of the patient. The supervised learning approach has been applied in other works, including [50, 51, 52], using several other learning methods. However, while a significant correlation exists between the inferred activity scores and the cognitive health status of the individual, those methods do not provide a description of the observed behavioral anomalies. On the contrary, the medical assessment would benefit from detailed knowledge of the abnormal behavior of the patient.

2. Types of sensing

(i) Unobtrusive sensing

Unobtrusive ADLs recognition relies on several sensors that detect the inhabitant's interaction with objects and furniture and his/her movements in the home. The measurements produced by those devices are continuously transmitted to a home gateway, in order to be used by behavioral monitoring applications.

(ii) Environmental sensing

Environmental sensors are cheap devices that unobtrusively monitor the interaction of the subject with the home infrastructure and his/her movements. The most common are binary sensors; i.e., sensors which produce as output "0" or "1" depending on the interaction being performed. Examples of such devices are magnetic sensors (e.g., to detect when doors or drawers are opened or closed) and pressure sensors (e.g., to detect when the subject sits on a chair). Passive InfraRed (PIR) sensors have been widely use to monitor the presence of the subject in specific home locations and to track his/her motion patterns. Coarse grained human movements have been monitored also by using air pressure sensors. Power meter sensors have been proposed to detect the usage of home appliances. Water usage can be monitored using flow meters or attaching low-cost microphones to the pipes of water distribution infrastructure.

3. Monitoring the interaction with everyday objects

Besides environmental sensors, smart-home activity recognition highly benefits from tracking the inhabitant's manipulations of everyday objects [28]. The majority of the solutions in the literature are based on a combination of RFID technologies and wearable devices [29, 30]. In those approaches, the subject needs to wear a glove which acts as an RFID reader. An RFID tag is hence attached to each object of interest in order to detect objects interaction. The main issue with this approach is that the monitored subject needs to continuously wear the glove. Moreover, it has been shown that RFID technologies are not reliable for a real deployment [31]. Finally, those methods only detect the generic interaction of the subject with the objects, thus not providing specific information about the performed manipulation.

4. Problem statement

Smart-home activity recognition systems proved to be effective for supporting the diagnosis and improving healthy aging. Various strategies have been proposed to devise effective and unobtrusive activity monitoring systems by exploiting pervasive computing technologies. A popular research direction for activity recognition consists in exploiting audio-visual information recorded by cameras and microphones with the help of sound, image and scene recognition software. However, those methods are sometimes tolerated in retirement residences, but much less in private homes due to the privacy issues that they determine. Other proposed activity recognition systems are mainly based on data acquired from body-worn accelerometers in order to recognize physical activities.

However, solutions based on wearables are critical: there is no guarantee that wristbands or pendants are constantly worn. There are also indications of a general adversity or disaffection of users to wearables targeted to healthcare related applications. Moreover, those methods are not well suited to recognize complex activities, like ADLs executed at home, which are characterized by the interaction of the individual with several objects and furniture. In view of the above problems, attention is focused on non-invasive sensor-based techniques which explanations are given through the following namely: unobtrusive sensing, activity and anomaly recognitions.

5. Research Objectives

The objective of this paper is to determine how knowledge-based and data-driven methods be combined in order to improve ADLs recognition?

As previously mentioned, data-driven methods are more scalable and they are robust against the intrinsic noise and uncertainty of sensors measurements, while they lack the capability of capturing important semantic relationships between sensor events and activities. On the other hand, knowledge-based methods capture very well the above-mentioned complex semantic relationships, but their specification is often too rigid to cope with the variability of execution of ADLs and to handle noise and uncertainty.

A novel hybrid ADLs recognition method was designed which uses knowledge-based conditions to refine the statistical prediction of a supervised learning algorithm. This method thus combines the strong points of both approaches in order to improve the recognition rate.

6. Methodology

Hybrid techniques to recognize ADLs

First technique: Supervised activity recognition through statistical and symbolic reasoning

This is hybrid method to recognize ADLs which is based on a combination of supervised learning and knowledge-based conditions to refine the statistical predictions. The proposed technique combines data-driven and knowledge-driven methods in order to exploit the strong points of both approaches. A machine learning algorithm is in charge of classifying, for each sensor event, the most likely performed ADL. In particular, time-based features are extracted from windows of consecutive sensor events to capture temporal relationships between events. A knowledge-based algorithm, named SMART AGGREGATION, is then in charge of grouping together those sensor events which most likely belong to the same activity instance and to correct possible mis-predictions produced by the machine learning algorithm. Comparison can be made experimentally the activity recognition ability of the approach to determine the superiority both on a lab-acquired dataset and on a real-home dataset.

Second technique: Unsupervised activity recognition through ontological and probabilistic reasoning

Unsupervised method is proposed to overcome the limitations of data-driven and knowledge-driven approaches. First, it does not need the acquisition of an expensive labeled dataset. Second, the activity model is based on general semantic relations among activities and smart-home infrastructure; hence, the model can be seamlessly reused with different individuals and in different environments.

Ontological reasoning is relied upon to derive necessary conditions about the sensor events that must occur during the execution of a specific activity in the current environment. This also enables to extract semantic correlations among fired sensor events and executed ADLs. Based on the semantic correlations, a statistical algorithm (named STATISTICAL ANALYSIS OF EVENTS) pre-processes sensor events to identify candidate activity instances, i.e., initial hypotheses about the start and end time of occurred activities. Ontological model can be translated in a Markov Logic Network (MLN), and perform probabilistic reasoning to refine candidate activity instances and check their consistency. MLN model is carefully crafted to support the recognition of interleaved activities. Extensive experiments with real-world datasets of ADLs performed by 22 individuals in two different smart home environments. Results show that, even using a smaller number of sensors, the performance of our unsupervised method is comparable to the one of existing methods that rely on labeled activity datasets.

7. Proposed System Architectures

Figure 2 shows an overview of our system. The smart-home monitoring system

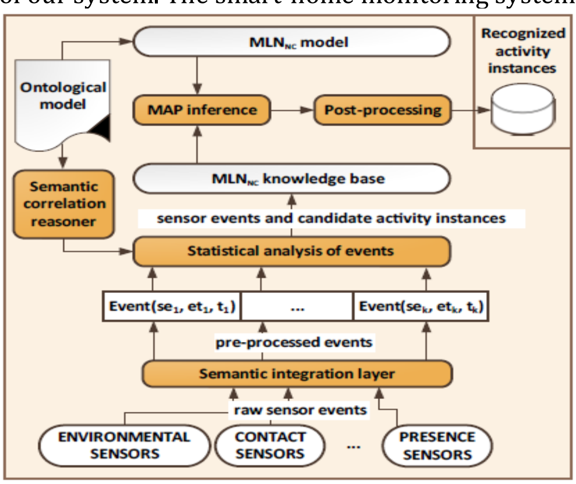

Figure 2: System overview

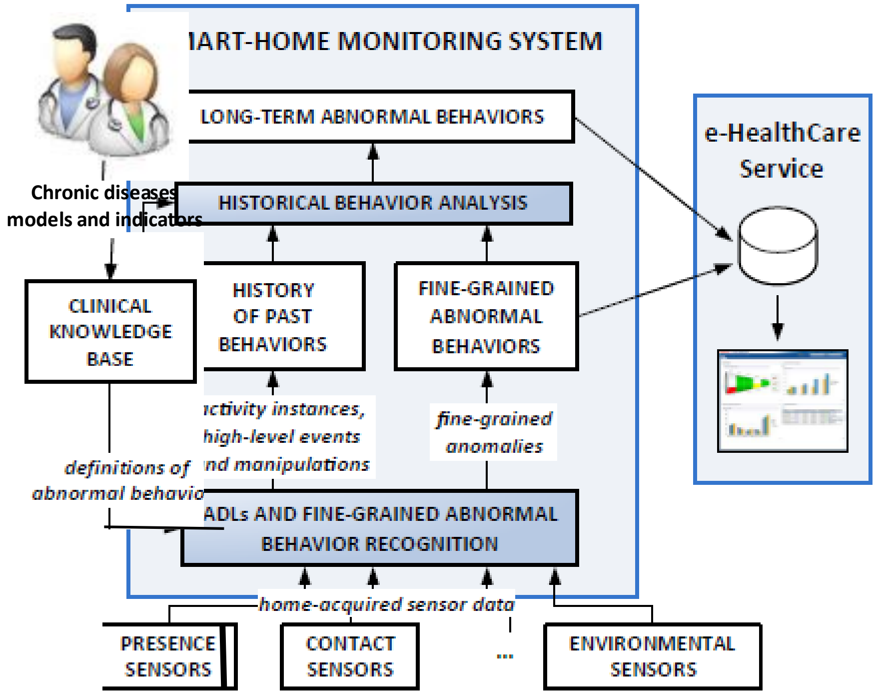

Figure 3: The architecture of our long-term analysis framework

8. Discussion

Monitoring the interaction of the subject with everyday objects is crucial to accurately detect ADLs. Moreover, clinicians are interested in monitoring how objects are manipulated in order to assess cognitive health. The current commercial low cost and low energy consumption multi-sensor devices that can be attached to everyday objects. A dataset of more than two thousands labeled manipulations while collected, report encouraging preliminary results on their recognition through machine learning techniques applied to accelerometer data collected from the objects.

It is believed that this study will contribute to the design of a sensing subsystem that could be effectively integrated into the smart-home environments used in several previous works on monitoring complex activities at home, independently from the algorithmic method being used, since object manipulations may be considered as simple events.

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