Artificial Intelligence in Medicine 67 (2016) 57–74

Contents lists available at ScienceDirect

Artificial Intelligence in Medicine

journal homepage: www.elsevier.com/locate/aiim

SmartFABER: Recognizing fine-grained abnormal behaviors for early detection of mild cognitive impairment

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ARTICLE INFO

Article history:
Received 23 July 2015
Received in revised form 26 October 2015
Accepted 29 December 2015

Keywords:
Mild cognitive impairment
Cognitive decline
Abnormal behavior detection
Activity recognition
Pervasive computing

ABSTRACT

Objective: In an ageing world population more citizens are at risk of cognitive impairment, with negative consequences on their ability of independent living, quality of life and sustainability of healthcare systems. Cognitive neuroscience researchers have identified behavioral anomalies that are significant indicators of cognitive decline. A general goal is the design of innovative methods and tools for continuously monitoring the functional abilities of the seniors at risk and reporting the behavioral anomalies to the clinicians. SmartFABER is a pervasive system targeting this objective.
Methods: A non-intrusive sensor network continuously acquires data about the interaction of the senior with the home environment during daily activities. A novel hybrid statistical and knowledge-based technique is used to analyses this data and detect the behavioral anomalies, whose history is presented through a dashboard to the clinicians. Differently from related works, SmartFABER can detect abnormal behaviors at a fine-grained level.
Results: We have fully implemented the system and evaluated it using real datasets, partly generated by performing activities in a smart home laboratory, and partly acquired during several months of monitoring of the instrumented home of a senior diagnosed with MCI. Experimental results, including comparisons with other activity recognition techniques, show the effectiveness of SmartFABER in terms of recognition rates.

1. Introduction

Independent living and pro-active healthcare are becoming strategic application areas for major research programmes all over the world, 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]. Other studies [3,4] observed how a closer examination of functional skills in individuals with MCI may enhance our understanding of the natural history and cognitive correlates of functional deterioration associated with dementia. They pointed out the limits of informant-based reports on subject abilities and proposed to extend well known performance evaluation tests (e.g., NAT [5]) with *subtle errors* recognition. Hence, from a medical point of view there is a clear interest in methods to monitor daily living activities of the elderly with the goal of identifying specific abnormal behaviors as indicators of cognitive decline.

Ubiquitous computing technologies coupled with intelligent data analysis have a recognized potential in the automatic recognition of IADLs. Indeed, 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 medical institution; hence, they incur in high costs

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http://dx.doi.org/10.1016/j.artmed.2015.12.001
0933-3657/

and cannot be applied on a continuous basis. Some of them deploy cameras and sensor networks in controlled environments and use video and audio for activity recognition: these systems are often perceived as too invasive for the elderly's privacy. Other works rely on continuous monitoring of low-level behavioral markers (steps taken, walking speed, ...) and trigger alarms whenever they detect situations sufficiently distant from the expected (modeled) behavior.

We have joined this research effort by designing and implementing SmartFABER, a pervasive system for fine-grained abnormal behavior recognition. SmartFABER is intended as a tool for clinicians for analysing the decline of functional abilities, supporting the diagnosis of MCI or even distinguishing between different MCI subtypes. SmartFABER has a sensor network component intended to be installed in the home of the senior and continuously acquiring data. Video and audio acquisition are excluded as too intrusive, while sensors are used to detect presence in particular locations, opening and closing of drawers, fridge and cabinet doors, use of appliances, as well as use of specific tools and food items.

With respect to other activity recognition systems, SmartFABER is designed to go beyond the recognition of the activity being performed by identifying the *anomalies* that can be observed in carrying out the activity (e.g., inappropriate timing in assuming food or medicine intake, improper use of equipment, unnecessary repetitions of actions). This is a challenging task for at least two reasons: (a) only certain anomalies or patterns of anomalies are relevant indicators for clinicians and they need to be properly modeled based on cognitive neuroscience expertise and (b) most approaches to activity recognition lack the ability to identify the fine-grained anomalies that are of interest to clinicians.

Our main contributions can be summarized as follows:

- We describe SmartFABER, a complete pervasive system that can be used by clinicians to identify and analyse even mild functional difficulties in elderly subjects performing daily activities at home;
- We explain the technical approach of SmartFABER that combines statistical and knowledge based methods to achieve the fine-grained anomaly detection goal;
- We experimentally compare the activity recognition ability of SmartFABER with a state of the art technique proposed in the literature showing its superiority both on a lab-acquired dataset and on a real-home dataset; we also show the improvements in anomaly detection over a preliminary version of our system;
- We report on the experience of deploying SmartFABER in the house of a senior diagnosed with MCI with the positive outcome of detecting most targeted anomalies with small number of false positives.

The rest of the paper is structured as follows. Section 2 discusses related work. Section 3 reports our model of activities and abnormal behaviors. Section 4 presents the SmartFABER method. Section 5 reports experimental results. Finally, Section 6 concludes the paper.

2. Related work

Activity recognition systems proved to be effective for supporting the diagnosis and improving healthy ageing [6,7]. In the literature, various strategies have been proposed to devise effective and unobtrusive activity monitoring systems by exploiting pervasive computing technologies [8]. 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. Audio data can be used to assess mood and other emotional conditions [9]. Speech and voice recordings have been used for diagnosis of early-stage dementia [10]. However, those methods are considered too invasive in a home environment, due to the privacy issues that they determine. Hence, in the following we restrict our attention to non-invasive sensor-based techniques.

2.1. Recognition of simple activities

Several techniques were proposed to recognize *simple* activities, which rely on data acquired from body-worn sensors and on the application of supervised learning methods [11,12]. Early attempts in this sense were mainly based on the use of data acquired from multiple body-worn accelerometers [13], possibly coupled with biometrical sensors and integrated in clothes [14], to recognize locomotion types and simple physical activities. A major limitation of these early systems is that they did not consider contextual information, such as current location, environmental conditions, and surrounding objects, that could be usefully exploited to improve the accuracy of recognition. Hence, other activity recognition approaches take into account the user's context by acquiring environmental data from several sensors [15]. For instance, in [16] the authors proposed the use of machine learning and data acquired from body-worn sensors (an ear microphone, sensor collar integrating electromyogram and microphone, and four upper body accelerometers) to accurately monitor food intake activities (movement, chewing and swallowing). However, being mainly based on body-worn sensors, those methods are not well suited to recognize more complex activities, like IADLs executed at home, which are characterized by the interaction of the individual with several objects and furniture.

2.2. Recognition of complex activities

The recognition of complex activities, like ADLs that we consider in our work, relies on the usage of sensors to detect the user's movements and the interaction with objects and furniture. For instance, in [17], 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 [18] to recognize activities based on features extracted from recent sensor events according to a sliding window. However, the recognition of complex activities turns out to be challenging using solely supervised learning methods. Indeed, complex activities are characterized by large inter- and intra-personal variability of execution, and it is very hard to acquire a sufficiently comprehensive training set to include most of the possible ways of executing activities. Hence, different frameworks for knowledge representation and reasoning have been investigated to appropriately model complex human activities by means of ontologies. In particular, description logics [19] have emerged among other symbolic formalisms, mostly because they provide complete reasoning supported by optimized automatic tools.

In [20], ontological descriptions of activities are used for the segmentation of sensor data streams acquired in a smart home. In particular, a shrinking time window algorithm is proposed to segment temporal sequences of sensor events, in order to discover sequences of events that match the ontological description of a human activity. Our approach is different: we recognize activity instances by aggregating the individual inferences of a machine learning algorithm, considering semantic conditions that the sensor sequence generated by an activity must satisfy. A Web mining technique to derive semantic dependencies among IADLs and used objects is proposed in [21]; those dependencies are used for activity segmentation. Our segmentation method considers more complex conditions about the necessary sensor events that must be observed during an activity execution. A further method to segment