Improving Supervised Classification of Activities of Daily Living Using Prior Knowledge

Anthony Fleury, University Lille Nord de France, France
Norbert Noury, University of Lyon, France
Michel Vacher, LIG Laboratory, France

ABSTRACT

The increase in life expectancy is producing a bottleneck at the entry in institutions. Therefore, telemedicine becomes a timely solution, which is largely explored to care after elderly people living independently at home. It requires identifying the behaviors and activities of the person at home, with non-intrusive sensors and to process data to detect the main trends in the health status. This paper presents the results of the study of prior introduction, in Support Vector Machine, to improve the automatic recognition of Activities of Daily Living. From a set of activities, performed in the experimental smart home in Grenoble, the authors obtained models for seven activities of Daily Living and tested the performances of this classification with introduction of spatial and temporal priors. Eventually, different results are discussed.

Keywords: Daily Living, Independent Living, Life Expectancy, Support Vector Machine, Telemedicine

INTRODUCTION

During the past 15 years, telemedicine, tele-monitoring and assisted living have been very active fields of research due to progress in sensors technologies and to the increasing performances of computing units (Noury et al., 2003; Chan, Estève, Escriba, & Campo, 2008). Moreover, the trend of the demography all over the world begins to be critical; nowadays the number of places in institutions ready to accept non autonomous elderly people is far lower than the demands. For this reason, researches in the field of smart sensors and smart homes try to offer new ways to assist the automatic monitoring of person, launching alarm when needed, either in case of a severe problem, such as a fall (Noury et al., 2007; Bourke & Lyons, 2007; Bourke, O’Brien, & Lyons, 2007), or in case of detection of a sudden modification in the habits of the person (Campo, Bonhomme, Chan, & Estève, 2010), which could indicate...
a problem. To monitor the person at home, we got interested in what the geriatrics try to follow up: the autonomy of the subject and particularly the Activities of Daily Living (ADL). This is the reason why our work focuses on automatic recognition of activities of daily living in a smart environment.

In the literature, we can find a large spectrum of smart home environments and experimental protocols to be used in activity recognition. For instance, Philipose et al. (2004) placed RFID tags on a large number of objects (more than one hundred) and a RFID receiver in a glove worn by the subject, and they tried to infer the activity that was performed considering the objects touched by the person; a Gaussian curve was describing the mean time of execution of each activity. They considered 14 activities and experimented on 14 persons. With Dynamic Bayesian Networks they obtained 88% in global detection accuracy. Hong, Nugent, Mulvenna, McClean, and Scotney (2008) also used RFID tags on foods and objects to create models for the activities “preparing a drink (cold or hot)” and “Hygiene”. Using Dempster-Shafer Theory, they selected the values of the “belief” and mass functions which made it possible to distinguish between both activities. Following this work, Nugent, Hong, Hallberg, Finlay, and Synnes (2008) also tested the impact of sensor failures on recognition using the evidential theory. Kröse, Kasteren, Gibson, and Dool (2008), in the CARE project, also tried to differentiate between two activities (“going to the toilets” and “exiting from the flat”) using the data from a lot of sensors (switch, environmental, etc.) and considering Hidden Markov Models for the classification. They achieved promising results and presented them on two elderly people (other studies only experimented on young individuals).

Some other sensors can be used, such as arrays of Force Sensing Resistors (FSR). Kim et al. (2009) set-up FSR on a sofa, a table, a toilet seat, on top of toilet bowl and in bed; they also placed an accelerometer-based sensor on the belt of the person. They aimed at detecting the start and end of the night with this combination of sensors. Simple On/off switches can also inform when objects are in used (Tapia, Intille, & Larson, 2004). The switches can transmit both their data and identifier (which corresponds to a location and an object). From this data, for each activity recorded, we can build a vector of features, which takes into account the use of a sensor or not, the way it is used, and if another sensor has been used before. The sensors are used on various doors, on specific objects such as cabinets, and also on electrical devices (microwave oven, TV, etc.). The authors tried to learn models for 35 activities using Naive-Bayes network with the described features. The results were presented for activities with a minimum number of occurrences (at least six) and for two individuals. The maximum number of activities was eight. The results presented an adequate classification ranging from 7% to 30%, dependent on the activity. Better results were obtained for an activity detected in the “best interval” (with a confidence interval of time before and after activity).

Tsukamato, Hoshino, and Tamura (2008) and Berenguer, Giordani, Giraud-By, and Noury (2008) tested the use of electrical signatures to detect various activities of daily living. Indeed, by using pattern recognition on the electrical network it is possible to infer which electrical appliances are being used, and when they are turned on and off. In their last paper, the same authors presented the detection of the activity “take a meal” on 18 elderly people whose flat were monitored.

Some other smart homes try to reduce the number of sensor; they mostly use video cameras and scene analysis. Libal et al. (2009) used 3 videos cameras, but also 24 microphones, to recognize 6 different activities in a smart environment. Audio and video were processed separately then fused. Then GMM were trained to recognize the activities from the vector of features extracted from both audio and video.
Related Content

Utilizing Mobile Phones as Patient Terminal in Managing Chronic Diseases
Alexander Kollmann, Peter Kastner and Guenter Schreier (2007). Web Mobile-Based Applications for Healthcare Management (pp. 227-257).
[www.igi-global.com/chapter/utilizing-mobile-phones-patient-terminal/31159?camid=4v1a](www.igi-global.com/chapter/utilizing-mobile-phones-patient-terminal/31159?camid=4v1a)

Mathematical Programming and Heuristics for Patient Scheduling in Hospitals: A Survey
[www.igi-global.com/chapter/mathematical-programming-and-heuristics-for-patient-scheduling-in-hospitals/163859?camid=4v1a](www.igi-global.com/chapter/mathematical-programming-and-heuristics-for-patient-scheduling-in-hospitals/163859?camid=4v1a)
Patent Issues in eHealth, Especially of North and South Problems on Telemedicine
[www.igi-global.com/chapter/patent-issues-ehealth-especially-north/65703?camid=4v1a](www.igi-global.com/chapter/patent-issues-ehealth-especially-north/65703?camid=4v1a)

Introducing E-Procurement in a Local Healthcare Agency
[www.igi-global.com/chapter/introducing-procurement-local-healthcare-agency/49987?camid=4v1a](www.igi-global.com/chapter/introducing-procurement-local-healthcare-agency/49987?camid=4v1a)