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Automated Generation of Models of Activities of Daily Living

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Abstract: In order to increase the safety of autonomous elderly people in their home, Ambient Assisted Living technologies are currently emerging. Namely, the recognition of their activities might be a way to detect eventual health problems, and can be performed in a Smarthome equipped with binary sensors. Hence, this communication aims at providing means to automatically generate a formal model of the Activities of Daily Living. A data mining approach in order to discover frequent habits of the observed inhabitant from a database of sequences of sensor events is proposed. Those frequent habits are then formally modelled using finite automata, leading to the construction of a map of habits mirroring the behaviour of the inhabitant. Such a model could then be used for online identification of habits, and even predictions of the upcoming behaviour. Results obtained on a case study are also presented.

Keywords: Activities of Daily Living, Discrete Event Systems, Data Mining, Automated Modelling

1. INTRODUCTION

The increase in life expectancy leads to an ageing population, whose needs in terms of health care are also increasing. In order to help the elderly to keep their autonomy at their home, emerging technologies for Ambient Assisted Living are being developed (Nehmer et al., 2006). The services provided by those technologies can be divided into three categories, defined in (Kleinberger et al., 2007): Emergency Assistance, Autonomy Enhancement and Comfort. Emergency Assistance is of crucial interest, and sustains the task of preventing health problems, or providing assistance should one occur. Monitoring the behaviour of the inhabitant allows for detection or even prediction of eventual irregularities. For that purpose, some tools are developed to identify the status of the inhabitant. The status could be split into the current position of the inhabitant, which can be evaluated by Location Tracking (Danancher et al., 2013), and the ongoing activity he is performing. A lot of works are hence dedicated to the recognition of Activities of Daily Living (*e.g.* waking up, showering, flushing the toilet, cooking . . .).

Those works require equipping the house with different kinds of sensors. In (Yu et al., 2009) cameras are used to detect whether the monitored inhabitant has fallen. In (Chernbumroong et al., 2013), wearable sensors are used to determine the posture and movement of the equipped inhabitant using accelerometers. In (Patterson et al., 2005), RFID sensors are used in order to detect which objects are being used by the inhabitant wearing the RFID reader. However, all those approaches are either intrusive or require the inhabitant to wear a special device. Another solution would be to use a Wireless Sensor Network, using a collection of various sensors with binary output, such as the universal switch sensors defined in (Intille et al., 2003). The network provides a flow of sensor events, each event containing very little information, but activities can be identified from a sequence issued of the flow.

In order to recognize activities out of a sequence of sensor events, which is assumed as a classification task (or supervised classification), all models share the same strategy : a learning phase on a set that has been studied by an expert, then the recognition phase, during which new set of data are classified, and parameters of the model are adapted in order to improve the recognition. The most classical classification model would be the Hidden Markov Model (HMM) (Cheng et al., 2010). Other models can be found in the literature. For instance, expert-designed boolean functions on the statuses of the sensors are used in (Botia et al., 2012), with an emphasis on the adaptation part. Expert models of activities are also designed in (Ros et al., 2013), each activity being described by an ordered set of action sequences, and the adaptation being achieved by learning automata. Data mining techniques are exploited in (Chikhaoui et al., 2011) to find frequent patterns in a sequence of events and compare them to expert models. Nevertheless, all those works focus only on classification, based on an expert knowledge.

The approach proposed in this paper is oriented towards providing a formal model of habits and activities discovered in a dataset of sequences, without *a priori* knowledge, hence in an unsupervised way (Dimitrov et al., 2010), and provides an automated method of building a map of the habits and activities of a monitored inhabitant. Such a model could be devoted to online real-time recognition of activities, and prediction when possible. Section II summarizes the approach. Section III deals with the data mining phase that discovers patterns in the dataset. Section IV presents the method and the formalism used to build the model of the patterns discovered. Section V provides an example of application to a case study.

2. OVERVIEW OF THE PROPOSED METHOD

The following method provides a way to get a formal model (a *map*) of all the habits of a monitored inhabitant, with possible applications such as real-time recognition of whether an activity is being executed or not, and prediction of what might be the next activity pursued. Such a model could therefore be used for the application of formal techniques such as diagnosis (in order to detect a faulty behaviour), and could detect either small incidents (such as an uncompleted activity) or slow behaviour alterations (such as an habit that disappears).

A smart home equipped with a binary sensor network will generate *events*, that correspond to a change of state of the sensors (which are assumed to be fault-free). Events are assumed to be not simultaneous, and an activity can thus be associated to a sequence of events. The behaviour of a human being is however arbitrary, hence multiple sequences of events can be images of the same activity, hardening the difficulty of building an expert model. A possibility is to use a training set (a few sequences that have already been observed), within which the sequences are still very different. Numerous observations would be required to depict all the possible sequences that depict the activity. Nevertheless, the sequences share sub-sequences, which are the fundamental basis of the activities, because they are very often played. Those frequent sequences would thus represent fundamental habits of the inhabitant.

The first contribution revolves around the discovery of these habits, which can be achieved by data mining methods (**Mining Step** of Figure 1). The dataset can stand in two forms. On one hand, it might be a unique sequence of events, within which frequent episodes can be found (Mannila et al., 1995),(Magnusson, 2000). A few days worth of observation could lead to a single sequence of events. On the other hand, one could use distinct sequences of events, as long as they represent the same temporal window, and compare each other in order to extract the habits. This last solution has been chosen. For the remainder of this work, it is also supposed that a single inhabitant is being monitored. Once the patterns have been found, habits can be identified within the set of patterns (**Identification Step** of Figure 1).

Then, the second contribution consists in the automated modelling of the discovered habits, which will lead to the building of a *map* of the habits of the inhabitant (**Automated Building Step** of Figure 1). This map allows for online recognition : when an event e occurs, the active states of the map change, leading to a set of habits that might be currently ongoing. The accuracy of the recognition remains out of the scope of this work.

It is worth noting that until the map is built, no expert knowledge has been injected in the model. The goal is to recognize frequent habits (that have already been observed and not expertly designed), instead of trying to split and classify every sequence observed into activities. Nevertheless, once the map is obtained, an expert can study it and determine which parts and which habits correspond to which activities. That part could also be helped by coupling the habit model with a location tracking model, thus getting information on both the location and the activity of the monitored inhabitant.

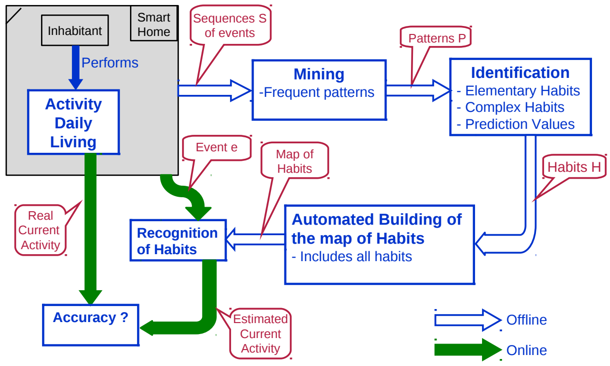

Fig. 1. Building a model from sequences of events issued of a Smart-Home

3. DISCOVERING PATTERNS

Sequence mining is a specific field of data mining that deals with the search for relevant patterns in sequences and strings. Most of the methods used in sequence mining look for frequent itemsets in databases, in order to discover association rules between items frequently found together. Such techniques would be the *Apriori* algorithm found in (Agrawal and Srikant, 1994), or the use of FPTrees found in (Han et al., 2000). Since the ordering of the items is irrelevant, those methods consider only databases that have been previously lexicographically ordered. However, in the case of a sequence of events, since we want to discover succession of events which would be images of habits, the order is of great importance and an adaptation is required. Based on the Apriori algorithm, the proposed algorithm is thus designed to find continuous ordered patterns.

3.1 Definitions

Definition 1. Sequence and events

Let $D = \{S_i\}_{i=1..n}$ be a database containing n sequences. A *sequence* S_i is an ordered list of events such as S_i=$[e^i_1, e^i_2, e^i_3 \dots, e^i_{l(S_i)}]$, where $l(S_i) \geq 2$ is the *length* of the sequence, and e^i_k is the k-th event of the sequence.

If Σ is the set of all the events that can be generated by the sensor network, then $\forall i \in [\![1, n]\!], \forall k \in [\![1, l(S_i)]\!], e^i_k \in \Sigma$.

Definition 2. Pattern

A *pattern* P is a sequence of events $P = [e^P_1, e^P_2, \dots, e^P_{l(P)}]$, where $l(P) \geq 2$ is the length of the pattern. An event is not enough to define a pattern. Hence, a pattern is said *of elementary length* when $l(P) = 2$, which is the minimum length.

A pattern P is contained in a sequence S_i if, and only if $\exists s \in [\![1, l(S_i) - l(P) + 1]\!]$, $[e^i_s, e^i_{s+1}, \dots, e^i_{s+l(P)-1}] = [e^P_1, e^P_2, \dots, e^P_{l(P)}]$, *i.e.* P is a