A Methodology for Household Appliances Behaviour Recognition in AmI Systems

Ovidiu Aritoni, Viorel Negru
Research Institute E-Austria
blvd. C.Coposu, 4, room 045B
300223, Timişoara, Romania
oaritoni@info.uvt.ro

Ambient intelligent systems (AmI) are characterized by the possibility to develop intelligent solution to contextual problems perceived from the ambient environment. Using perceptional data from various sensors , data which is collected over a period of time, these systems can understand an ambient environment and they try to solve problems that may appear. The process of understanding the ambient environment does not mean the simple collection of data from the various sensors, this process sometimes necessitates the aggregation of data and the recognition of certain special behaviors. The identification of activities is done ,in most cases, by receiving data from several types of sensors [5]. For example, if the system is to recognize when a person is doing some sort of physical exercises, data from the following sensor types are used: EKG, temperature, proximity sensors, accelerometer, light sensors etc. To successfully recognize behaviour various techniques are used, this field of computing research being the main target of numerous studies. The Hidden Markov Model (HMM) is a probabilistic model used in the process of recognizing activities with the help of data collected from various sensors [9, 3, 8]. Activities may also be recognized by other techniques such as database exploration, data correlation and other data mining techniques [6]. In order to add new activities the context in which these new activities occurred must be known [2]. This article will be focused on the understanding of ambient environment using the identification of certain behaviours. In the research project DEHEMS [1], the contextual understanding of the ambient environment comes from the data collected on the usage of house hold appliances. This usage is being monitored by the use of a single type of sensor namely a sensor designed to measure AC current consumption. The system uses on stream of data, from the AC sensor, which is used in this study to determine and analyse the behaviour of house hold appliances.

In the paper [4] the Bit-Watt system is used to recognize appliances based on there (previously known) power signature. The system presented in this article in contrast to the system presented in the paper [4] will be able to identify appliances connected to the environments (ex. house) power grid. The Bit-Watt systems sensor is placed between the appliance and the electric socket, thus being able to identify only the appliance on which the sensor is placed.

In our study there is only one AC sensor that generates one stream of data which represents the power consumption of all house hold appliances. There are no other sensors as in the Bit-Watt system thus only one sensor for the entire household. The purpose of this study is to determine the state in which all house hold appliances are at any given time with the help of the data stream from the AC sensor.

Our system has to know in advance the model and make of all appliances present in a household this will enable the system to determine the various scenarios of current consumption. The definition of his scenario of current consumption is realized by identifying each appliance in turn from the single data stream being sent by the AC sensor. Another problem that needs to be addressed is that of subdividing the data stream from the AC sensor into different data sets, for each appliance.

During the process, a repository of signatures for the different appliances present in the household will be used. Every appliance will be described using a directed graph in which the states of an appliance are represented by the nodes in the graph. If between the two states A and B a connection exists the transition from state A to state B is possible. The construction of this repository of power signatures can be made using empirical data by measuring the power signature each appliance in part. These signatures will be modelled with the use of a directed graph. The repository can also be constructed using pattern recognition techniques on the data [7]. The discovery of a certain pattern repeating cyclically will lead to the conclusion that we have an appliance described by this pattern. These patterns will be stored in the system and will be used in the process of analysing the behaviour of household appliances.

In order to describe successfully the power consumption scenarios it is necessary to decompose the primary data stream into smaller data sets which describe the states in which a particular appliance is. To accomplish this, we use a Greedy algorithm and matching mechanisms. Every value of the data stream will be decomposed into other values, this process being an ongoing one within the system. The values resulting through decomposition and the different power signatures the matching coefficient is computed which in turn will be used to detect which appliance is in use and what it's current state is. Greedy decomposition of certain values will be made in the inflexion points of the data stream. The points situated before and after the inflexion point will be used to check the conclusion reached from the analysis of the inflexion point. One or more tuples will result from the data stream decomposition. Constructing and generating associations between these tuples will be realized using heuristics which are determined empirically from experimentation. For example some appliances can have a predictable and linear behaviour, one example are refrigerators which switch on and off a few minutes at a time depending on the setting and outside temperature.

The purpose of this study is to construct scenarios regarding the usage of house hold appliances using the data stream from the AC sensor mounted on the household electrical grid. These scenarios will specify : the order in which appliances are running, the moment when an appliance starts, the time moment when an appliance stops running and the moment when an appliances normal functioning is interrupted by certain events. These informations are necessary in a smart home, because it enables the system to respond to the inhabitants needs. Using these scenarios some predictions can be made by the AmI system. Utilizing these predictions some improvements may be made that will increase the level of comfort and/or power usage efficiency of a smart home. For example if the time in which the user usually goes to sleep can be inferred, the AmI system can turn off all necessary house hold appliances during the time the user sleeps without the user directly instructing the system to do so.

Acknowledgement

The research leading to these results has received funding from the European Community's Seventh Framework Programme FP7/2007-2013 under grant agreement N^0 No224609 *DEHEMS*, and by the Romanian *DEHEMS-RO* project *RO-PNII-20-EU/11.06.09*. The views expressed in this paper do not necessarily reflect those of the DEHEMS consortium members. Further information on DEHEMS can be obtained from http://www.dehems.eu.

References

[1] http://www.dehems.eu.

[2] A. K. Dey. Understanding and using context. *Personal Ubiquitous Comput.*, 5(1):4–7, 2001.

[3] W. Huang, J. Zhang, and Z. Liu. Activity recognition based on hidden markov models. In *KSEM'07: Proceedings of the 2nd international conference on Knowledge science, engineering and management*, pages 532–537, Berlin, Heidelberg, 2007. Springer-Verlag.

[4] T. Kato, H. S. Cho, D. Lee, T. Toyomura, and T. Yamazaki. Appliance recognition from electric current signals for information-energy integrated network in home environments. In *ICOST '09: Proceedings of the 7th International Conference on Smart Homes and Health Telematics*, pages 150–157, Berlin, Heidelberg, 2009. Springer-Verlag.

[5] A. Kofod-Petersen and J. Cassens. Explanations and context in ambient intelligent systems. In *CONTEXT'07: Proceedings of the 6th international and interdisciplinary conference on Modeling and using context*, pages 303–316, Berlin, Heidelberg, 2007. Springer-Verlag.

[6] S. Lühr, G. West, and S. Venkatesh. Recognition of emergent human behaviour in a smart home: A data mining approach. *Pervasive Mob. Comput.*, 3(2):95–116, 2007.

[7] S. E. Rombo and G. Terracina. Discovering representative models in large time series databases. In *FQAS*, pages 84–97, 2004.

[8] D. Sanchez, M. Tentori, and J. Favela. Hidden markov models for activity recognition in ambient intelligence environments. In *ENC '07: Proceedings of the Eighth Mexican International Conference on Current Trends in Computer Science*, pages 33–40, Washington, DC, USA, 2007. IEEE Computer Society.

[9] T. van Kasteren, A. Noulas, G. Englebienne, and B. Kröse. Accurate activity recognition in a home setting. In *UbiComp '08: Proceedings of the 10th international conference on Ubiquitous computing*, pages 1–9, New York, NY, USA, 2008. ACM.