A Methodology for Household Appliances Behaviour Recognition in AmI Systems

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***Abstract*—The actual research in green computing tries to understand the human behavior and how appliances are used in households. We propose, in this paper, a software prototype which can be used to understand the household appliances' behavior. Our architecture uses heuristic functions and pattern matching mechanisms in order to achieve this goal.**

***Keywords*-curent-cost sensor data-stream, appliance recognition,behavior recognition, heuristics.**

I. INTRODUCTION

Ambient intelligent systems (AmI) are characterized by the possibility to develop intelligent solutions for the contextual problems perceived from the ambient environment. Using data from various sensors, which are collected over a long time period, these systems can understand the 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, using data from several types of sensors [1]. For example, if the system try to recognize whether a person makes a sort of physical exercises, data from the following sensors types are used: EKG, temperature, proximity sensors, accelerometer, light sensors etc. To successfully recognize the human behavior, 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 [2], [3], [4]. The activities may also be recognized using other techniques such as database exploration, data correlation and other data mining techniques [5]. This article will be focused on the understanding of ambient environment using the identification of certain behaviors. In the research project DEHEMS [6], the contextual understanding of the ambient environment comes from the data collected on the usage of household appliances. This usage is being monitored by the use of a single type of sensor namely a sensor designed to measure alternative curent (AC) current consumption. The system uses the data stream, from the AC sensor, to recognize and analyze the household appliances behavior.

The paper presents an ”intelligent” current-cost sensor which recognizes the scenario about how the appliances from a house are running. We concentrate on the next section to determine on positioning the paper in the research area of intelligent curent-cost sensors. Thereafter, we present the architecture and the main idea of our system. We conclude the paper with the important fields of the future work and a discussion about how to validate our system.

II. RELATED WORK

The Bit-Watt system is used to recognize the appliances from a household, using in this process the devices power signature (previously known) [7]. The system presented in this article in contrast to the system presented in [7] will be able to identify the appliances connected to the household power grid. The Bit-Watt system's sensor is placed between the appliance and the electric socket, thus being able to identify only the appliance on which the sensor is placed.

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

The proposed system result is a scenario that describes the behavior of all the appliances from a household. It is important to know when and how often is used a specific appliance. The purpose of the DEHEMS project [6] is to develop recommendations about how to improve the home energy efficiency. An objective of the project is to detect the human actions or the users habits that increase the energy usage inefficiency. Using the appliances' behavior we can obtain information about the human behavior: the output of our system is used for the household residents behavior recognition. The human behavior analysis and the correlation with the appliances behavior help us to detect the actions or habits that reduce the energy efficiency. The statistics about the appliances most used in a household, are also useful in the recommendation process. The DEHEMS project [6] is part of the open-living labs experience [8]. We use the feedback of the household residents in order to improve our

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system, and the sensors data received from the living-labs houses.

III. Architecture

Our system has to know in advance the models of all the appliances from a household. This will enable to determine the various scenarios of current consumption. The definition of this 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 specific data sets, for each appliance.

During the process, a repository of signatures for the different appliances present in the household will be used. The construction of this repository of power signatures can be made using empirical data by measuring the power signatures for each appliance in part. A signature is described using a finite-state machine. We build the repository using patterns recognition techniques on the data [9]. 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 analyzing the behavior of household appliances.

Our system needs to know the producer and type of all the appliances from the household. Another existing approaches use a smart current-cost sensor to acquire data about the individual appliance. This means that we have to install numerous devices if we want to monitor the states of all the appliances. In this situations the cost of current-cost sensors network installation and maintenance will be higher than in our proposal. Our goal is to propose an "intelligent current-cost sensor" which minimize the cost of deployment, using a single sensor instead of more sensors. Each household has a current-cost sensor that provides monthly the total power consumed. Our system uses this current-cost sensor or a special wrapper-sensor.

Also, our system uses a "central" repository that stores the signatures of all the appliances. The proposed system is a module of a recommendation system for the energy efficiency improvement. This recommender system consists of two parts: a central-server and local subsystems for each household. The server-side provides web-services for data-storage about each household. A central database stores data about each household: the number of appliances, a list of all the appliances, appliances signatures, the current-cost sensor datastream, and other important information. The amount effort that is required to train our system is reduced using the central-server. Also, the central server is useful when we want to compare the appliances behavior and help us to detect the devices' malfunctions. For each household we have an instance of the proposed system.

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 state in which a particular appliance is. To accomplish this, we use a Greedy algorithm [10] 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 is current its state. 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 real world. For example some appliances can have a predictable and linear behavior, one example are refrigerators which switch on and off a few minutes at a time depending on the setting and outside temperature.

The present application achieves a breakdown of the total electric consumption of devices that can operate in a house. We use a heuristic function defined by people at home through a questionnaire. The heuristics are used only when there is uncertainty in the detection pattern (eg. several matching patterns). Our model is based on heuristic functions that help us to reduce the problem complexity. A heuristic function returns for a specified time moment a list of devices that can run at the moment and a probability for each device to run at this time:

$h : T \longmapsto \chi, h(t) = \{(d_1, p_1), (d_2, p_2), ..., (d_n, p_n)\}$

where:

t is a time interval

d_i is a device

p_i is the probability to use the device d_i at that moment.

$\chi = \Delta \times P$, Δ is the ensemble of all the devices and p_i is a probability, $p_i \in P = [0, 1]$

Also we use another heuristic functions, likely the association rules:

$h^* : T \times \Delta \longmapsto \chi$

$h(t, D) = \{(d_1, p_1), (d_2, p_2), ..., (d_n, p_n)\}$

The h^* heuristic inform us that if at the current moment the device D is running, after, on the t time interval can run the devices $d_i, i = 1, ..., n$.

The heuristic values are based on a questionnaire. The users will answer to a lot of questions about their living style. Using these answers we calculate the heuristic values. The heuristic function and the use of the central "repository" of appliances signature provide a large scalability for our system.

The purpose of this study is to construct scenarios regarding the usage of household 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. An example of such scenario is:
7.00 LightBedroom ON
7.02 LightBathroom ON
7.08 LightBeedrom OFF 100%
7.08 CoffeeMaker ON
7.12 LightBathroom OFF 100%
7.12 Refrigerator ON
7.16 CoffeMaker OFF 87%
....
10.22 PEAK
....
As one can see, the light from bedroom is ON at 7.00 and OFF at 7.08, and we conclude that the light was run normally 100%. The coffee maker runs from 7.08 to 7.16, but it has run only 87% normally. This coefficient is calculated as the similarity factor between the nominal time-serie (from the repository) and the actual time-serie. At 10.22 we have a PEAK event on the household electrical grid.

This information is 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. Using the 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 when the user usually goes to sleep can be inferred, the AmI system can turn off all necessary household appliances during the time the user sleeps.

Our system uses as input the power readings stream of a user's device and produced as output: determination of the malfunctioning of the device (health status) and other statistics. Our first goal was to define a set of rules, so that, given a set of energy readings, would evaluate the health of a device and pinpoint regions of faulty power usage. A set of reading has at its core two most evident states: ON and OFF. This information developed our first rule in evaluating device consumption. Thus, before going any further, we must extract the actual usage that characterizes the ON state of the device. Further information has to be provided about each specific type of device in order to effectively determine health status, and such information has to be accessible. Given that, as a general rule, the correct function of a device, as observed only by consulting the values representing the power consumption, has to fit between some boundaries: the maximum power consumption and minimum power consumption, the former, as observed earlier, having to reflect the ON state of the device. The device specifications sometimes include the maximum and minimum power consumptions. However, for the purpose of this project, these were taken from energy usage patterns. Using our system we analyzed the power consumptions of our laptops and successfully created charts that show that the deviations are negative, which means the devices operate under the minimum power consumption specification, making it optimal.

IV. Conclusion and Future Works

We use in our study a current-cost sensor to collect data from usually devices such as refrigerators, computers, multimedia devices, etc. The heuristics are extracted via a questionnaire applied to more than 1000 inhabitants from rural and urban areas from the Banat region of Romania. The evaluation of the proposed prototype will be done using intelligent current-cost sensors for each appliance. These sensors will collect data for each appliance and in this way we will obtain a scenario for each appliance from the household. A sum of all these appliances scenarios will be compared with our results (the behavior of our appliances). We use a comparation between these scenarios for the evaluation of our prototype. Furthermore, we can use in the evaluation process a curent-cost sensor data simulator, in order to compare the simulation scenario with the output of our prototype.

Our software prototype uses finite-state machine as model for each appliance's behavior, and heuristic functions to reduce the complexity of the problem. This approach consists in observing the specific pattern of each device. After this, we identify these patterns in the total consumption using our heuristics.

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References

[1] 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*. Berlin, Heidelberg: Springer-Verlag, 2007, pp. 303–316.

[2] 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*. New York, NY, USA: ACM, 2008, pp. 1–9.

[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*. Berlin, Heidelberg: Springer-Verlag, 2007, pp. 532–537.

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[4] 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*. Washington, DC, USA: IEEE Computer Society, 2007, pp. 33–40.

[5] S. Lühr, G. West, and S. Venkatesh, "Recognition of emergent human behaviour in a smart home: A data mining approach," *Pervasive Mob. Comput.*, vol. 3, no. 2, pp. 95–116, 2007.

[6] "http://www.dehems.eu [retrieved: May 10, 2011]."

[7] 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*. Berlin, Heidelberg: Springer-Verlag, 2009, pp. 150–157.

[8] "http://www.openlivinglabs.eu [retrieved: May 10, 2011]."

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

[10] A. R. Teixeira, A. M. Tomé, and E. W. Lang, "Greedy kpca in biomedical signal processing," in *Proceedings of the 17th international conference on Artificial neural networks*, ser. ICANN'07. Berlin, Heidelberg: Springer-Verlag, 2007, pp. 486–495. [Online]. Available: http://portal.acm.org/citation.cfm?id=1778066.1778123