Efficient Appliances Recognition in Smart Homes Based on Active and Reactive Power, Fast Fourier Transform and Decision Trees

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Abstract

Western societies are facing demographic challenges due the rapid aging of their population. In this context, economic and social issues are emerging, such as an increasing number of elderly in need of home cares and a shortage of caregivers. Smart home technology has imposed itself as a potential avenue of solution to these important issues. Its goal is to provide adapted assistance to a semi-autonomous resident in the form of hints, suggestions, reminders, and to take preventive actions, for instance turning off the oven, in the case of an emergency. The main scientific challenge related to this kind of assistance concerns the problem of recognizing, in real time, of the on-going activities of the resident in order to provide punctual guidance for the completion of everyday tasks. In the literature, the majority of the proposed solutions for activity recognition exploit a complex and expensive network of intrusive sensors (i.e. infrared, radio-identification, electromagnetic, pressure, cameras, etc.). A recent and innovative way of performing activity recognition is based on the monitoring of electrical household appliances by analyzing the electrical signals solely at the main panel. This approach is less intrusive and required only one sensor. In this paper, we present new advancements in that field, which take the form of an efficient method for recognizing electrical appliances within smart home based on the analysis of the features of the load signatures (active and reactive power, FFT) and on the use of the C4.5 algorithm to extract decision trees. This method has been implemented and tested in real smart home infrastructure showing that it is economical, simple and efficient.

Introduction

Western societies are facing demographic challenges due the rapid aging of their population. In the next decades, the population of elders will triple [2]. It is a direct consequence of the falling birthrates and the rising life expectancy. This issue leads to a shortage of human resources, including medical staff for home cares, and to increasing number of cognitively-impaired people in need [3]. Cognitive deficits lead to difficulties completing daily activities and to the need of assistance for staying at home in safety. Most cognitively-impaired people want to stay in their home as long as possible. Thus, assistive technology can be seen has a potential answer to this challenge.

Smart home technology [4] has imposed itself as an avenue of solution to these important issues. Its goal is to provide adapted assistance to a semi-autonomous resident in the form of hints, suggestions, reminders, and to take preventive actions, for instance turning off the oven, in the case of an emergency. The main scientific challenge related to this kind of assistance concerns the problem of recognizing, in real time, of the on-going activities of the resident in order to provide punctual guidance for the completion of everyday tasks [4, 5].

Most existing recognition approaches rely on distributed sensors (RFID, electromagnetic, pressure mats, infrared, etc.), which are often expensive, heterogeneous and complex to install in existing infrastructures [15]. Also, there are intrusive and they need maintenance. Also, multiple solutions have been proposed using cameras because they allow obtaining very accurate information [16]. Although the information provided is very rich and interesting, there is an ethical issue using this type of sensor in the context of smart home. The cameras are intrusive and they infringe on the privacy of residents.

Another interesting way to perform activity recognition is based on the real-time detection and monitoring of electrical household appliances by analyzing the electrical signals solely at the main panel. This approach is less intrusive, less expensive and required only one sensor that can be easily installed in an existing infrastructure. This technique is named Non-Intrusive Appliance Load

Monitoring (NIALM). Generally, NIALM techniques are developed in order to provide energy efficiency solutions for electrical power consumption. Furthermore, the monitoring of the electrical signals requires only one sensor at the main panel of a home or a building. We decided to adopt this method for activity recognition because it is relatively cheap compared to the multi-field sensors approach and it is non intrusive. Moreover, there are only few labs which explore this technique for the recognition of the daily living activities in smart homes.

In our previous work [1], we presented an activity recognition algorithm based on the monitoring of the electrical events in the smart home, that is, the real-time detection of which appliance is turned on or off and when it is in operation. This detection was done by observing the fluctuations of the active and reactive power at the main electrical panel of the smart home when a particular appliance was in use. For each appliance, these fluctuations were recorded at the opening and at the closing to constitute what is called the load signature. Indeed, through very hard work, we obtained the load signature of each appliance. Next, we implemented our detection algorithm based on the load signatures obtained and we improved the detection rate by adjusting the parameters by a trial-and-error method.

It is worth noting that other research teams have developed different detection methods based on two-dimensional space representation (active and reactive power) [6, 7], on three-dimensional space representation (active and reactive power and the third harmonic) [8] or with more than three features such as the wavelet transform of the current signals [9, 10]. However, these other detection methods are not adapted to our activity recognition context. They require too much time of computation (real-time is not possible). Moreover, they necessitate the use of high sampling rate power sensor which are very expensive (up to twenty times the cost of our sensor).

In this paper, we propose an extension to our previous work [1]. Although the detection rate was very high, this method was not quite interesting to deploy in other smart homes due to the amount of time needed to be set up. Furthermore, another limitation was in the discrimination between two different appliances with similar load signature (active and reactive power). Thus, we decided to add the information provided by the Fast Fourier Transform (FFT) of the current signals [11] to our previous algorithm and to make use of the C4.5 classifier algorithm [12] to generate, automatically from the dataset of the load signature of each appliance, the best decision tree for the detection of which appliance is turned on or off. Once the decision tree is generated, it is automatically implemented to become the new detection algorithm. Proceeding this way allows the quick deployment of the detection algorithm regardless of the smart home and this detection algorithm can be further combined to an activity recognition algorithm using the information coming from the use of electrical appliances [15, 16].

Firstly, we present some important definitions and concepts appearing throughout the paper. Secondly, the procedure used to extract the load signature of each appliance is described. Thirdly, we provide the decision tree generated by the C4.5 algorithm. Finally, we discuss the detection rate attained by this new method.

Concept and Definition

Load Signature

The load signature is the electrical behavior in transition state and in steady state which we can observe in the time and frequency domain. The different parameters are the voltage, the current and the power [9]. The main idea is to identify the load signature of each appliance present in a home.

Non-Intrusive Appliance Load Monitoring

Non-Intrusive Appliance Load Monitoring (NIALM) [6] describes a process to detect changes of state in the voltage and the current supplying a house or a building. Obviously, these changes of state create significant differences of power (active and reactive) that can be monitored by an electric meter installed at the main panel. NIALM techniques are mainly developed in order to provide solutions optimizing the electric power consumption.

Formal Definition of loading features

Each appliance is provided with specific operation characteristics. We considered the active power (P) and the reactive power (R) given by equation (1) and (2):

$$P = \sum_{k=0} P_k = \sum_{k=0} V_k I_k \cos(\varphi_k) \qquad (1)$$

$$Q = \sum_{k=0} Q_k = \sum_{k=0} V_k I_k \sin(\varphi_k) \qquad (2)$$

Here, V and I represent the voltage magnitude and respectively the current magnitude, φ_k denotes the phase angle between these two measurements and k coincides with the harmonic order.

Moreover, using the Fast Fourier Transform (FFT), the harmonic contents of the current can be obtained. The FFT of a signal $c(n)$ is computed in the following way:

$$C_k = \sum_{n=0}^{N-1} c(n) e^{-\left(\frac{2\pi i n k}{N}\right)}, \quad k = 0, \dots, N-1. \qquad (3)$$

Here, C_k is the output of the transformation (an imaginary number). N represents the number of samples used for the computation of the FFT and k denotes the rank of the harmonic. Finally, the magnitude of the FFT of rank k is given by the complex modulus of C_k .

The perfect supply network only has the fundamental harmonic and the disturbed supply network has a fundamental and harmonics. Thus, the quality of the supply modifies the magnitude of the appliances current harmonics. The electronic parts of the appliances create current harmonics and contribute to the harmonics magnitude. Nevertheless, these characteristics permit us to perform the difference between appliances which are similar in power consumption. So, we decided to integrate the FFT of the current as features for the detection of appliances.

Method for activity recognition

The method developed for activity recognition is based on our previous work [1] (power analysis) with the addition of the information provided by the Fast Fourier Transform of the current signals. The first step (learning step) is to establish a database containing the load signature of each appliance in the smart home. The second step is to make use of the C4.5 classifier algorithm to extract a decision tree from the database which will further allow us to do the detection of which appliance is turned on or off. The extraction of the decision tree is performed through the Weka software environment.

Load signature attributes extraction algorithm

This subsection presents the algorithm used to extract the load signatures attributes through turn on and turn off operations of each appliance present in the smart home.

Input: The data readings from power analyzer
Output: Attributes of appliance load signature

Do
  Compute ΔP and ΔQ between consecutive time t_1 and t_2 on the three-phases electrical power
  If ΔP or ΔQ of a line-to-neutral voltage is > threshold
    Event start
    Store the FFTs amplitudes
    Store the time t_2
  End

  Add ΔP and ΔQ at the sum
  Register the maximum ΔP and ΔQ
  Register the maximum ΔP and ΔQ
  Compute the FFTs mobile averages
  If the Event time > 2 seconds
    Compute the Δ of FFTs
    Send the load signature characteristics for learning or the recognition
  End
Until an appliance is switched on

Algorithm 1: Algorithm used to extract attributes of each appliance load signature

The learning step consists to turn on and turn off several times appliances to obtain all attributes of their load signatures. These attributes are listed in Table 1. The power analyzer provides 60 measures per second of the current, voltage, active power, reactive power and the FFT of the current signal (up to 32th harmonics) for each three phases.

All data are stored automatically in a Attribute-Relation File Format (ARFF) file. All the selected attributes for the detection are presented in the next section along with the algorithm used to generate the decision tree.

Appliance Identification

The real-time identification of appliances is based on their specific load signatures which are characterized by the values of the attributes listed in the following table:

P1		
Steady State	Maximum Peak	FFT amplitude
SS-PL1 SS-QL1	Peak-PL1 Peak-QL1	FFT-L1-1 FFT-L1-2 FFT-L1-3 FFT-L1-4 FFT-L1-5 FFT-L1-6
P2		
Steady State	Maximum Peak	FFT amplitude
SS-PL2 SS-QL2	Peak-PL2 Peak-QL2	FFT-L2-1 FFT-L2-2 FFT-L2-3 FFT-L2-4 FFT-L2-5 FFT-L2-6
P3		
Steady State	Maximum Peak	FFT amplitude
SS-PL3	Peak-PL3	FFT-L3-1

SS-QL3	Peak-QL3	FFT-L3-2 FFT-L3-3 FFT-L3-4 FFT-L3-5 FFT-L3-6

Table 1: List of the load signature attributes for appliances recognition

Here, P_i is the supply phase number, $SS - PL_i$ and $SS - QL_i$ denote, respectively, the steady state active power and reactive power on the supply number phase i, $Peak - PL_i$ and $Peak - QL_i$ are the active power peak and the reactive power peak when the appliance is just turned on or off. Finally, $FFT - L_i - j$ is the FFT amplitude at steady state on the phase i of order j.

The ARFF file containing the values of the attributes of each appliance's load signature (on/off) is used by the C4.5 algorithm through the Weka software environment. The C4.5 is a supervised classification algorithm based on the ID3 algorithm. The C4.5 algorithm uses a divide-and-conquer approach to build a decision tree [13]. In our case, this algorithm is applied to determine the attributes (as well as their values) which are the most discriminative for the detection of the turning on and off of each appliance. In other words, the C4.5 algorithm predicts the output value y_i of the cost function versus the characteristic input value x_i. The decision tree can be build using a divide-and-conquer approach in conjunction with the entropy test given by equation (4), the gain of information defined by equation (5) and the split of information described by equation (6):

$$Info(D) = -\sum_{j=1}^{k} p(D,j) \cdot log_2\big(p(D,j)\big) \qquad (4)$$

$$Gain(D,T) = Info(D) - \sum_{i=1}^{k} \frac{|D_i|}{|D|} \cdot info(D_i) \qquad (5)$$

$$Split(D,T) = -\sum_{i=1}^{k} \frac{|D_i|}{|D|} \cdot log_2\left(\frac{|D_i|}{|D|}\right) \qquad (6)$$

Here, D denotes the dataset, D_i holds for a subset of the dataset, k is the number of classes, $p(D,j)$ corresponds to the proportion of cases in D belonging to the j^{th} class and T is the test outcome.

The decision tree obtained from the load signatures attributes of each appliance (on/off) shows the positive impact of adding the FFT (up to 6^{th} harmonics) of the current signals for the detection of which appliance is turned on or off. Figure 1 shows a part of the detection tree generated by the C4.5 algorithm. Finally, this decision tree has been implemented and the efficiency of the detection based on this tree has been evaluated.

```
SS-PL3>-393
|   FFT-L2-6<=-3
|   |   SS-PL2<=1071: ToasterON
|   |   SS-PL2>1071: ElectricKettleON
|   FFT-L2-6>-3
|   |   FFT-L2-6<=9
|   |   |   SS-PL1 <=148
|   |   |   |   SS-QL1<=-169: RangeHoodFanOFF
|   |   |   |   SS-QL1>-169
|   |   |   |   |   SS-QL1<=135
|   |   |   |   |   |   SS-PL1<=-788: CoffeeMakerOff
|   |   |   |   |   |
|   |   |   |   |   |   SS-PL1>-788
|   |   |   |   |   |   |   FFT-L1-1<=-788:
|   |   |   |   |   |   |   CoffeeMakerOFF
|   |   |   |   |   |   |   FFT-L1-1>-408
|   |   |   |   |   |   |   |   FFT-L1-5-
|   |   |   |   |   |   |   |   <=153:MixerOff
|   |   |   |   |   |   |   |   FFT-L1-5->153
|   |   |   |   |   |   |   |   |
|   |   |   |   |   |   |   |   |   …
```

Figure 1: Part of the decision tree obtained by the C4.5 algorithm.

Experimental Protocol

Experiments have been done in LIARA laboratory. The lab is a smart home infrastructure with 100 square meters surface. It contains about a hundred of sensors and effectors: power analyzer, infrared sensors, pressure mats, electromagnetic contacts, light sensors, RFID tags and antennas, iPad, IP speakers, HD television and lights. Data acquired by sensors are sent in real-time to the Dell industrial server for processing thanks to the APAX 5570 automata. More precisely for the electric part, the Lab has a smart modular power analyzer WM40 96 from Carlo Gavazzi's company. This power analyzer measures the voltage, the current, the active power, the reactive power, the apparent power and the power factor on the three supply phases. Furthermore, the WM40 96 also computes the FFT (up to 32th harmonics) of the current and the voltage signals for each phase. The sampling rate is approximately 1920Hz. However, we only have access to 60 measures per second because the WM40 96 writes with this speed in its register.

The main objective was to measure the rate of correctly recognized appliances by using the decision tree obtained from the training step where the load signature of each appliance was characterized by specific values of active and reactive power and the added attributes, that is, the FFT of the six first current harmonics.

Consequently, the first step was to determine the set of all possibly recognizable appliances used by a resident living in the smart home. It is worth noting that due to the perturbations of the supply network, appliances consuming less than 125 W cannot be detected. Table 2 shows the list of the appliances considered in our study. The second step aimed to learn the specific values of the load signature attributes of each appliance. To do so, we turned on and off each appliance approximately 50 times and we stored in an ARFF file the specific values of the attributes constituting the load signature of the appliances. Next, we applied the C4.5 algorithm to our dataset through the Weka software in order to extract the required decision tree. The resulting decision tree is automatically implemented to become the detection algorithm. Finally, the last step was to test the efficiency of the resulting detection (recognition) algorithm. Thus, we turned on and off each appliance 20 times and we compute the rate of correctly identified appliances.

Results & Discussion

The implemented algorithm extracts information from the WM40 96 sensor. If it detects a significant variation of the active power (more than 125 W), it sends the list of the measured specific attribute's to the decision tree which associates instantly the appliance that has been turned on or off. In our previous work, we obtained a great recognition rate, that is, almost all appliances were recognized (turned on and off) 100 % of the time. In the current work, we obtained a similar global rate of recognition. The tested appliances are presented in Table 2 with their identification number (ID number).

ID number	Appliances
1	Toaster
2	Electric kettle
3	Stove burner no. 1
4	Stove burner no. 2
5	Microwave
6	Vacuum
7	Oven
8	Coffee maker
9	Blender
10	Dryer (mode high)
11	Dryer (mode low)
12	Range hoof fan
13	Mixer

Table 2: ID of each appliance

It is important to note that LIARA lab is integrated in the university building. Thus, the electrical network is shared between them. Consequently, the electrical signals are often fluctuating (+/- 125 W). Although these fluctuations influence the detection, we still obtain very good classification results for the decision tree. The classification rate is 93.4397% of true positive (527 instances correctly classified) and 37 instances incorrectly classified. Furthermore, the time to build the decision tree model takes 0.04 second while in our previous work, it took many hours to build the model.

To test the detection algorithm which consists in the implementation of the decision tree generated from the dataset containing the load signature of appliances, we have repeated 20 times the turn on and turn off operation for each learned appliances. Figure 2 illustrates the percentage of recognition attained in the current work as well as in the previous work for several appliances. The recognition rate of the range hood fan is better in the current work than in the previous work. Conversely, the one of the mixer is worst in the current work than in the previous work. This difference can be explained, for the mixer, from the confusion in the recognition of the on and off states.

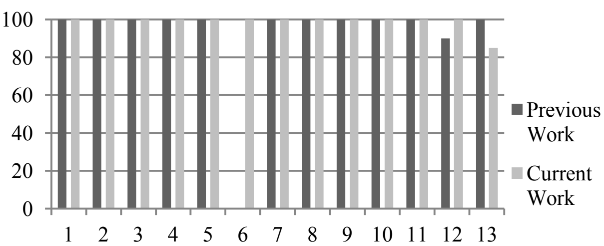

Figure 2: Comparison of the percentage of recognition between our previous work and the current work for each tested appliances (ID number)

The results obtained by using this method show the benefit of having added the information provided by the FFT (six first harmonics of the current signals) for the which plays a central role in the recognition process (see Figure 1). Moreover, once the step of learning the load signature of appliances is done (requiring only few hours) the generation of the decision tree by the C4.5 algorithm through Weka software necessitates less than one second of computation and the implementation of that decision tree is automatically done also in less than a second right using of the Weka software to generate a decision. The comparison with other works is difficult because of the different context of application and the goal aimed. Despite this fact, Table 3 shows results obtained in other works. Specifically, the number of appliances recognized, the method used and the rate of recognition are given.

Conclusion

In this paper, we presented a fast method to recognize electrical appliances within smart home based on the analysis of their load signatures characterized by active and reactive power and the FFT of the current signals (six first harmonics) and on the use of the C4.5 algorithm to extract a decision tree which becomes the recognition algorithm. This method is economical, simple and efficient for the recognition of the electrical appliances in operation (on/off) from the main panel of a home and can be further easily integrated into an algorithm of recognition of daily living activities. One of the main differences with our previous work relies on the automatic generation of the decision tree which eases the quick deployment of the detection algorithm regardless of the smart home.

Authors & Technique	Total of features / identified devices	Accuracy (%) of identification
Lei Jiang et al. [11] Extraction of P, Q, FFT information with the aggregated Eigen value calculation Classification algorithm : SVM	4/9	90.6%
Francesca Paradiso et al. [14] Split range with the number of point and the power Artificial Neural Network Optimization parameters Levenberg-Marquardt algorithm	10/8	95.3%
Yulieth Jimenez et al. [12] Extraction of power information and the standard deviation using the current value aggregation and the S-transform Classification algorithm : SVM	7/5	94.1%
Rahimi et al. [4] Mahalanobis distance	2/7	100%
Our works Extraction of P,Q,FFT informations Classification Algorithm : C4.5	4/13	98.9%

Table 3: Comparison between works on appliances recognition

Nevertheless, this method can be optimized. In our future works, we will integrate new appliances to our recognition algorithm and we will also test an iterative decision tree generation algorithm. Thus, the recognition algorithm will be able to modify itself if needed and this will make our approach more robust and reliable.

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