Activity Recognition in Smart Homes based on Electrical Devices Identification

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ABSTRACT

Activity recognition constitutes the key challenge in the development of smart home assistive systems. In this paper, we propose a new algorithmic method for activity recognition in a smart home, based on load signatures of appliances. Most recognition approaches rely on distributed and heterogeneous sensors (ex. RFID), which are intrusive require complex installation, deployment and maintenance. On the other hand, most applications of appliance load monitoring (signal analysis) refer to the energy saving and the costs reducing of energy consumption. Consequently, our proposal constitutes an original application and new algorithmic method based on steady-state operations and signatures. The extraction process of load signatures of appliances is carried out in a three-dimensional space through a single power analyzer, which is non-intrusive (NIALM). We have rigorously tested this new approach by conducting an experiment in our smart home prototype by simulating daily scenarios taken from clinical trials previously done with Alzheimer patients. The promising results we obtained are presented and compared to other approaches, showing that, with an exceptionally minimal investment and the exploitation of relatively limited data, our method can efficiently recognize activities of daily living for providing assistive services.

Categories and Subject Descriptors

C.0 **[Systems Application Architecture]**, C.2.1 **[Sensor networks]**, K.4.2 Social Issues (Assistive technologies for persons with disabilities), H.1.2 [**User/Machine Systems**].

General Terms

Algorithm, Experimentation, Performance, Reliability, Human Factors.

Keywords

Activity recognition, smart home, load signature, nonintrusive appliance load monitoring (NIALM).

1. INTRODUCTION

Facing the problem of population aging, researchers are now investigating new technological solutions by developing smart home systems able to assist silver-aged residents in their house.

A smart home [14] aims to help its resident performing his activities of daily living (ADL), thus increasing his autonomy. The first key challenge of this technology is to be able to correctly identify and monitor the current ongoing activity of daily living (ADL) of its resident. Most existing recognition approaches [13] rely on distributed sensors (RFID, electromagnetic, pressure mats, infrared, etc.), which are often expensive, heterogeneous and complex to install in old infrastructures. Also, there are intrusive and they need maintenance. On the other hand, appliance load monitoring (electrical signal analysis) was investigated for the purpose of energy saving and the costs reducing of energy consumption [1]. It only requires one power analyser installed at the entrance electrical panel. The variation in the power consumption in the house can be represented as events, which can be used for activity recognition. From an electrical point of view, each common appliance in a house has a specific load signature, which varies with the time and its mode of utilization [1]. This signature allows determining the energy consumption, the frequency, the time and the exact moment of use of an appliance. The real challenge with respect to the appliance load monitoring is the identification of the load signatures according to the operation mode of the appliances, because they must be accurate and distinct to avoid overlap and therefore the misidentifications. Initially, the methods used to accomplish this task were intrusive, but actually most researchers in this area proceed by means of non-intrusive methods [1-14]. Several of them suggested monitoring methods for extracting the characteristics of devices so as to obtain load signatures in two-dimensional spaces [3, 6-8], in three-dimensional spaces [5, 11] or with more than three features [2, 9]. Usually, the two main features that are extracted are the active and reactive power necessary to the operation of the appliance. However, in some cases, the harmonic feature of the appliance (load signatures in 3-D) is analyzed. Moreover, there exist three types of approaches to describe the load signatures: the technique with steady-state operations [3, 7], the process with transient operations[1] [5] or a mixture of both methods [2, 9, 12]. The systems that are reserved for these previous methods are provided with analyzers with diverse sampling rates, which introduce a gap between the accuracy of each approach. Most of them involves major costs and sometimes require additional sensors or equipment to get greater precision for feature extraction, which generally introduces a certain degree of intrusiveness [3, 5, 6] and important inconveniences [7-8] that our suggested method avoid while delivering a particularly high precision.

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[1] Sometimes the transient operations appeals to turn-on transient energy (PQU_T)

In this paper, to contribute solving the recognition issue using electrical signal analysis, we propose a cheap NIALM system for identifying load signatures of appliances with the aim to ensure the recognition of activities. Our conceptual contribution consists in developing a NIALM system for the activity recognition of patients with Alzheimer's disease within a smart home through the extraction of the load signatures represented by three features of the appliances and based on power analysis at the steady-state. Secondly, our practical contribution is a complete implementation of this system within a real smart home environment provided with a power analyzer which is centralized in a single point, either the main electric panel, and the monitored household appliances which are used daily. Finally, we rigorously tested our load appliance monitoring system with some real scenarios of activities with some household devices among the 16 monitored appliances to demonstrate its efficiency in our use context. Our procedure then enables analysis of the power consumption of appliances to recognize ongoing activities and to detect unusual situations within a smart home for silver aged and cognitively impaired people. This scope remains of huge importance given the growth visibly manifest of the aging population and the need for autonomy that is felt among people with cognitive impairment in our society. Thus, considering our method that involves low investment and demonstrates accuracy comparable to the approaches to quality, it appears to be a very interesting technological advance with a great potential to be developed.

The sections of this document are structured as follows. The second section defines some terms and concepts. The third explains the features used for our method. Then the fourth presents the both phases of our new contribution based on steady-state signatures in a two-dimensional space. Subsequently, the fifth describes the implementation of our system and our experimental methodology. In the section VI, we analyze and compare the test results. Finally, in the last section, we elaborate on potential development opportunities in the near future through our contribution.

2. CONCEPT AND DEFINITIONS

2.1 Load Signature

The load signature corresponds to the specific electrical behaviour of an individual appliance/piece of equipment when it is in operation [2]. Typically, the variables considered are the voltage, the current and the power. In this way, each appliance is represented by its own waveform of power consumption versus the time.

2.2 Smart Home

In fact, the smart home is a house or an apartment equipped with sensors (e.g.: motion detectors, RFID tags, pressure detectors, etc.) [7] to track the person residing there and detect atypical situations through monitoring and then be able to intervene and assist the person visually or auditorily. Moreover, some household items are equally endowed of RFID tags that allow to locate and to identify them inside the apartment. Thus, the intelligent home is a house designed so as to introduce various forms of artificial intelligence that ensure the monitoring and care to inhabitants independently.

2.3 Activity Recognition

The activity recognition is currently an area of growing research and particularly in regard to smart home [7, 13] because we seek to provide a form of autonomy for individuals who require increased daily monitoring. This is actually a method for determining the routine of a person which is based on a sequence of observed events by means of multiple sensors usually found in smart home. Also, when the activity recognition is considered with time and space, it can warn us of the strangeness of a situation according to the reading returned by the sensors and/or analyzers.

2.4 Nonintrusive Appliance Load Monitoring (NIALM)

The acronym NIALM describes a process to detect changes of state in the voltage and the current supplying a house or a building, which directly influence the power difference. Electric meters with NIALM technology are frequently used by utility companies to review the specific uses of electric power consumption in different homes [1]-[4]. As a rule, with the NIALM, the hardware and the meters used to monitor the behaviour of appliances are transparent to end-users. Indeed, the measures are frequently taken at the entrance of the facility (e.g.: main electrical service entrance). In this way, the implementation of NIALM reduces sensor expenses by using relatively few sensors. Thus, with NIALM there are fewer components to install, maintain and remove [3]. In addition, in [5], we note that the procedures of NIALM are divided into two, that is to say, those analyzing the steady-state and those that focus on the transient detection.

3. FORMAL DEFINITIONS OF LOADING FEATURES

Each electrical appliance is provided with operation characteristics that are specific. In what concerns us, we focused on two main features related to power consumption. We therefore undertook the study of active and reactive power of each appliance that could be used within the house. Following are the formulas of the active power (P), expressed in watts, and reactive power (Q) whose unit is the VAR:

$$\mathrm{P} = \sum_{k=0}^{\infty} P_k = \sum_{k=0}^{\infty} V_k\, I_k \cos(\varphi_k) \tag{1}$$

$$\mathrm{Q} = \sum_{k=0}^{\infty} Q_k = \sum_{k=0}^{\infty} V_k\, I_k \sin(\varphi_k) \tag{2}$$

Here, V and I correspond to the magnitude of the measure of voltage and current respectively, φ is the phase angle between these two measurements and k coincides with the harmonic order.

Besides, we also considered the three-phase lines on which the devices were operable on the assumption that these will be permanently connected. For instance, the oven that operates on two phase power is easily recognizable, since most appliances use current on a single phase power of the three-phase lines.

In [7], Rabini et al. describe briefly the 3 types of loading for the household appliances. These can be resistive, inductive or capacitive. In the event that the device has a pure resistive load, the current and voltage are in phase. However, when a device is manufactured of capacitive and/or inductive elements, this introduces a phase shift between the current signal and the voltage. In case of the capacitive loads, the voltage is delayed with respect to the current while the contrary happens for inductive loads [7]. In other words, the Q for the transition from steady-state of the system to the "on" state of an appliance is nonzero.

4. NEW METHOD FOR ACTIVITY RECOGNITION

We have developed a relatively simple and inexpensive NIALM algorithm, which is based on a method with steady-state operations where the load signatures are studied in a three-dimensional space. For this, we propose a core algorithm to establish and complete a representative load signature database, which based on the P and Q averages, for each appliance used within the smart home. Hence, our method is divided into two phases: the first identifies the load signatures of appliances and the second focuses on the recognition of devices through their load signatures. Therefore, the following section discusses our approach to create database for load signatures, our algorithm for the activity recognition in connection with the appliances operated and the related issues.

4.1 Algorithm for Extracting Load Signatures

The first stage, to be suitable for performing the activity recognition from the identification of devices during use, was to create an algorithm which detects when each appliance is turned on and off within a house. Consequently, in order to build a data sheet for household devices, we used a non-intrusive module measuring only RMS values of P and Q in Eq. 1 and Eq. 2. The possibility to obtain a complete power consumption waveform for each appliance [2, 6, 9] was therefore discarded as a result of limited number of measurement samples provided by our power analyzer. Thus, we created an algorithm to describe the load signatures of each appliance from 3 characteristics:

- ΔP and ΔQ during an on/off event
- The line-to-neutral that supplies the appliance

First, our algorithm reads an instantaneous measurement of the P and Q on each line of three-phase lines at time $t_{1.}$ Then, it repeats exactly the same process at time t_2 that has only a single clock tick more than t_1. Afterwards, we inserted a function with conditional structure which does the difference between power measurements taken at time t_2 and these at time t_1 until a transient state is noticed on at least a single-phase electric power, namely a positive ΔP sufficient to exceed the predetermined threshold. At this point, we are virtually guaranteed that there is an appliance that is put into operation. We then look for the maximum value of instantaneous P reached to obtain the maximum positive delta, because, sometimes, it takes a few measures after the switching on before reaching the maximum amplitude. If there was a significant ΔQ during the switching on, the algorithm tries also to find the absolute maximum variation for Q.

Next, the function redoes the same experiment, but replacing the power values at time t_1 by the maximum values found, until we measure a significant negative ΔP (after turning off the device) on the same single-phase electrical power or on the same two-phase electrical power to get the data about on/off of the device in operating. Therefore, the algorithm logs the data collected during the event detection.

4.2 Special Features Processed By Algorithm of Phase 1

As concerns the Q handled by the algorithms 1 and 2, it contains more constraints since the variation may be positive or negative when an appliance is switched on according to the phase angle (see formula 2). Thus, we must take account of the two cases raised when we add the conditions of the conditional structure and not just assume that the Q will be respectively positive and negative to the “on” and “off” positions. We then work with the values of deltas in absolute when it comes to make comparison of these latter with their threshold depending on their corresponding line-to-neutral.

With regard to verifying the values of maximum Q, we must first validate whether the delta, during the switching on of the device, is positive or negative. If it is a positive value, we need to measure a power value above the maximum Q stored in the array named *maxPowerR*, depending on the line-to-neutral voltage supplying the appliance. Conversely, to achieve a value called “maximum” in a context of absolute values, our power analyzer must read a power value lower than the Q kept in reserve in the array *maxPowerR* according to the line-to-neutral voltage where it is observed. This latter should essentially supply the appliance to be worthwhile.

In addition, the fact that the power supply is connected to the power system of the university constitutes a supplementary challenge for our experiments. Indeed, when we monitor the general power consumption of each line-to-neutral of our smart home in laboratory, we note that there are lots of fluctuations in the P of our system. It is probably due to the fact that the power system of a building, as a university, is in great demand constantly [5]. Consequently, these undesirable fluctuations complicate the extraction of the P characteristic of the lowest resistive loads, because a distinct change in the P could be wrongfully considered as an event (on/off) and it could merely be a distinct fluctuation. For this reason, we have to impose a threshold high enough to avoid confusing a fluctuation with a real change of state of a device. Thus, few devices such as lights are excludes of the load signature database in reason of their slight energy consumption.

Further conditions, not mentioned, were added to the source code as a result of fluctuations of energy data read by the power analyzer and to respect the particularities of some appliances that will be addressed later in the document. Nonetheless, for the sake of simplicity, and from this perspective, these were not included in the pseudo-code.

4.3 Activity Recognition Algorithm

For the second phase of our method, the recognition phase, we repeated the algorithm of phase 1 for creating a database of load signatures related to each appliance. In fact, we created a list, equivalent to a database, that contains the household appliances whose we determined the load signature previously. The algorithm that we propose is a model that follows the line of the work of [7]. Nevertheless, there remains a considerable difference compared to our approach; it is the amount of appliances readily monitored. This is due to the installation of NIALM system that is really dissimilar of ours: the current and voltage were measured at the input of the power bar instead of the main electrical panel, which limits the number of monitored devices to 7 in total and is not necessarily convenient for the end-users.

4.3.1 Load Signature Database of the Algorithm

Firstly, to match on/off event with the right load signature, we have created a database from data gathered in the experimental part 1. More explicitly, we created, from the Table 1, objects named *MonAppareil* that we have added in the ArrayList called *MesAppareils.* These contain the following useful attributes: name of appliance, thresholds for P and Q, means of P and Q (ON/OFF), No. of lines to neutral used. Then, the list *MesAppareils* will serve as database.

4.3.2 Development of the Algorithm of Phase 2

The main idea of our algorithm (see Algorithm 1) is that changes in the on/off status of appliances can be detected by variation in the power consumption of individual line-to-neutral power supplies, because this method proves to be more complex since there are many important fluctuations in the system within our university building. With this procedure, we achieved to associate a detected event to an appliance from the load signature database according to the features of this. An event is defined by a considerable ΔP or

ΔQ, i.e. when the difference between two consecutive measurements is superior to the threshold. As previously mentioned, this power variation is calculated for each line to neutral. Consequently, if a significant change is computed, an object is added, with its detected features, to the list which contains the appliances in operation. Useful features are attributed to the object of the appliance in use such as the times when appliance is switched on and off, the No. of line-to-neutral, etc.

An essential aspect of our procedure is the conditions related to the detection of events: on or off. In fact, we assume that it is almost impossible to be in presence of two distinct events on an interval of less than 1 second. Therefore, we put a restriction that prevents the algorithm to add a novel event to the list if it has elapsed less than 1 second since the last event.

"On" event: according to power changes we expect to see on each line-to-neutral, these last one will have their own threshold for both P and Q. Thus, when the last detected event occurred at least one second ago, a ΔP which is measured from line-to-neutral voltage is greater than the set threshold corresponding to the adequate line-to-neutral and there is not "off" event previously detected, we come to the conclusion that an "on" event just happens.

"Off" event: in connection to "off" event detection, our algorithm looks for a considerable negative ΔP which will be stored in an attribute of the specific object created for this kind of event. Besides, this value will be replaced by a smaller one until the P becomes in a state which is considered steady; it is evaluated on few measures.

Next, we compare objects which are already turned on with the characteristics collected for the "off" event with the aim to associate this recent event with the most fitting object. To this end, we make the sum of measured changes at the switching on and at the recent switching off of the device, if features as the line-to-neutral are the same, so as to get a result close to zero. Unavoidably, when we sum the opposite values, we are supposed to obtain a value really near of zero. Therefore, when we find an object conforming to these criteria, we log the "off" time and the other useful information resulting from the "off" event. Finally, after the "off" event, the object features are copied in a report and removed from the list of appliances in use and the "off" object is reset.

Also, we add a particular condition for the "off" event for the refrigerator, i.e., if a relatively low change is observed on the line 3 to neutral less than 20 minutes after the "on" event, we will never consider the refrigerator compressor turned off, because we have discerned that, the refrigerator compressor, commonly, is shut off after 30 minutes in operation.

4.3.3 *Misinterpreted changes*

However, as abovementioned, it happens that a power fluctuation is considered on/off event. To prevent this kind of error, when we review the list of devices in uses, if the ΔQ is still negligible and the ΔP, on the suitable line to neutral, is negative after less than 60 measures, we remove this object from the list. The same consequence is applied when only a considerable ΔQ is computed and then, after 10 measures, there is still not important ΔP on the same line to neutral than the measured ΔQ and the difference between the current measure of Q and the measure at the steady-state, before the "on" event, is below the set threshold. Thus, it reduces the confusion between fluctuations and real event detections.

```
Input: The electrical data readings from power analyzer
Output: Monitoring report
Read ΔP and ΔQ
Do
Compute ΔP and ΔQ, between the current value and the maximum value at the steady-state on each phase of the three-phase electrical power
If the ΔP or ΔQ of a line-to-neutral voltage is > threshold and the last "on" event was detected for more than 60 measures
    There is an appliance switched on
    Store the time t where device is turned on
    Add the object to the list ListeAppareilFonction with its features
End

If a device has been turned on
    Check from P that the appliance is not switched off
If there is an appliance still in use for less than 60 measures
    Compute the maximum ΔP and ΔQ on appropriated line-to-neutral voltage
Else if an appliance is still in use for 60 measures
    Compare the appliance's features with those of the objects in the database to identify the name of the appliance in use
Else
    There is an appliance switched off
    Store the time t (time where device is turned off)
    Store the data (ΔP, ΔQ and time) from "off" event of the appliance in another object MonAppareil
    Compare the previous features with these of all the objects in ListeAppareilFonction until the features fit with those of an object in use
    Write information about on/off events of appliances in monitoring report
End
End
Until the monitoring is stopped
```

Algorithm 1. Pseudocode for recognizing the appliances by load signatures.

4.3.4 *Appliance Identification*

To identify the appliance after it is turned on, it is best to get the reached maximum variation, in terms of absolute value, regarding to power consumption. This point will help us to match correctly the detected appliance with the most appropriate from database. Indeed, our algorithm to generate the database extracts the maximum power consumption of individual appliance. So, if we want to respect the suggested threshold, we have to proceed in a similar way to gather our data which are used for the comparison. As aforementioned, we opted for this deadline of 1 second to get the absolute maximum change, because we hypothesized that the probability that both devices are powered up with less than 1 second interval was near zero.

In this way, 60 measures after the "on" event, our algorithm attempts to identify the object turned on with the most appropriate in the load signature database. In fact, it verifies the «equality» of this object with the objects put in storage in the database. It can happen that two or more objects from the database are described of "equal" to the features of the recent "on" event. Thus, having doubts as to the appliance identity, we attribute all the object names.

Nonetheless, it can occur that none object from the load signature database represented in Table 1 is fitting with the new event describing the switching on of a household device. In this case, the object resulting from this event is labelled as unknown. To remedy this situation, we call a function which allows, if the object of the "off" event meets the conditions of basis features with an object from the load signature database, to compute the Euclidean distance (*ED*) from the values stored in the database and to stock it whether this one is the lowest:

$$ED = \sum_{i=1}^{N} (y_i - \widehat{y_i})^2 \quad \textbf{(3)}$$

Hence, y_i and $\widehat{y_i}$ respectively represent the value of the feature *i* of the object and the mean value of the characteristic *i* of this appliance. Then, we keep the name of the appliance for which we achieved the best result for the Euclidean distance.

4.3.5 Monitoring Report

Moreover, our algorithm runs continuously, so we don't have to find a sophisticated method, such as those based on advanced optimization techniques involving neural network, genetic algorithm, and dynamic programming [10]-[12], to disaggregate the total load on a snapshot that can occur at any time. In fact, we dissect permanently the measured data from the analyzer to perceive and classify the on/off event.

This particular point of our algorithm will be helpful to record the daily habits of inhabitants and to note the singular patterns that differ from their routine. Indeed, a new object is created by the algorithm when an event is detected. So, we just have to store each new object in a list and then, to copy in a file all the components required to monitor the activities of the inhabitant of the smart home what it allow us to intervene if necessary. The file then acts as a report on the activities of the inhabitant providing the moment when an appliance is switched on and off and, thereby, the period of use. In fact, for each detected event, the file adds a recording line, which contains the device, its state, the date and time when the event occurred as well as the period of use, which is deduced from information about time that is recorded. Hence, this activity recognition algorithm could be used to supervise the daily activities of a person in loss of autonomy and to guide her by artificial intelligence and/or human means.

5. IMPLEMENTATION AND METHODOLOGY

In order to implement our experiments, we set up in our laboratory infrastructures a NIALM system that monitors the electrical consumption at a single electrical source, either the main electrical panel of the laboratory in university, resulting in low costs regarding the installation and maintenance. In fact, we have implemented a smart modular power analyzer (model: WM30 96) from the Carlo Gavazzi's company. This one can send to our computer server the voltage, the current, the P and Q, the frequency and the power factor. A sequence of code in our algorithm can then store this data in database on our server, because all these devices work on the same network. Moreover, it solely treats the RMS values; sending is approximately 60 data/second in our database. An important point to mention is that the appliance load monitoring, within our smart home in laboratory, depends only of this analyzer. It means there are not other sensors or equipment for this process. Furthermore, the appliances that were monitored were the following: a stove, an oven, a kettle, a toaster, a range hood fan, a coffee maker, a microwave, a hair dryer, a blender, an electric mixer, a stereo and a refrigerator compressor. The schema of Figure 1 shows the architecture of the system.

With regard to our methodology, it was divided into two phases. The first was designed to obtain data for building our database for our algorithm to recognize the appliances. Then, we evaluated the accuracy of the algorithm for the activity recognition when only one appliance is operating and after, with many appliances operating simultaneously.

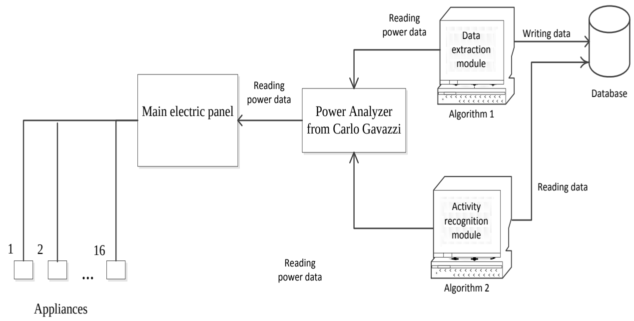

Figure 1: Implementation schema of our NIALM system

5.1 Experimental Protocol for the Phase 1

To achieve the data acquisition for our Algorithm 2, we have carried at least 50 consecutive tests of switching on and off for each individual device or mode operating, among the 16 monitored appliances/modes (see Table 1), within a smart home. It means that only one appliance was operating at the same time. First, we turned on this appliance and after, we turned it off. We repeated this process 50 times with the same appliance. It helped us to identify specific features and/or to target devices with features less well-defined.

In fact, these experiments consisted of extracting the maximum ΔP and ΔQ during the on/off events. Thus, the algorithm read the data from power analyzer. Therefore, the data were logged during the event detection. Inevitably, the values of opposite events are supposed to be almost identical in absolute value.

Finally, at the time of the logging of all data collected, we got 2 distinct files, one for P and the other for Q, which looked like Figure 2. Here each data line corresponded to an event of an appliance. Also, it is considered that for the refrigerator compressor, only 5 tests were performed given the considerable time before the complete turning off of this one.

	A	B	C	D	E	F
1	Time at ON/OFF	Time at maximum power	Delta WL1	Delta WL2	Delta WL3	Delta WS
2						
3	2012-06-11 09:01	2012-06-11 09:01	21,9240417	1556,35962	7,1255188	1585,4093
4	2012-06-11 09:01	2012-06-11 09:01	-3,94659424	-1527,05069	-1,00564575	-1532,00305
5	2012-06-11 09:01	2012-06-11 09:01	-34,1582947	1571,34766	-23,0940247	1514,09534
6	2012-06-11 09:01	2012-06-11 09:01	28,8290405	-1609,39886	0,10671997	-1580,46301
7	2012-06-11 09:01	2012-06-11 09:01	5,52389526	1604,0376	6,40447998	1615,96619

Figure 2: File for deltas of active power

Subsequently, we had to estimate the central value of the gathered data distribution for the deltas of power. So we opted to calculate the mean of these power changes that have been recorded and to set the threshold for the algorithm of appliance recognition according to the values obtained at limits assuming that we could gauge power changes that are slightly larger or smaller when the appliance is turned on or off.

5.1.1 Undetected Load Signatures

There are some appliances which the features were impossible to extract, to form the load signature, due to a lower change during an on/off event. These appliances are the television, lights, personal computer, etc. After doing some research [2, 11], we found that the extraction of the harmonic feature (even low-order harmonic) could be an interesting solution for this problem and to add few of these appliances to our list. Nevertheless, to execute this plan, we need to have the appropriate hardware which involves additional costs.

5.1.2 Inconstancy of the Variation of Reactive Power

Moreover, we noticed during the tests that some appliances presented an inconstant variation about their Q feature. It occurs only when the Q doesn't stabilize at the switching on of an appliance. In reality, for these cases, the Q appears only the time of a peak when the appliance is turned on and off. To overcome this problem, we did more ON/OFF tests for theses appliances to analyze this kind of behaviour and to suggest two profiles of objects for the activity recognition algorithm. Essentially, the list will contains twice the same objects, but with a difference pertaining to the Q range.

5.2 Results and Analysis of the Results of Phase 1

The obtained results after calculating the average (on/off events) for ΔP for each device and those for the average of ΔQ are shown in Table 1. In the Figure 3, the different appliances studied are depicted according to their specific ΔP and ΔQ. Note that the identifiers (IDs) and the values that are used correspond to those of the devices listed shown in Table 1. However, for the appliances which operate on two phase power we made the addition of the two values, which gave us the total reactive power and the total active power which are essential to turn them on.

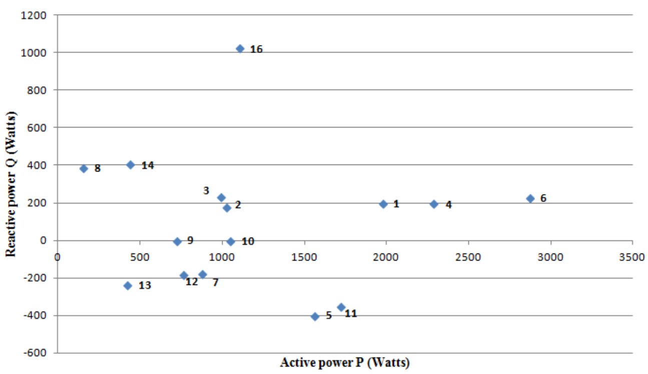

Figure 3: *PQ* diagram of appliances in the database.

Nevertheless, we had to make a thorough analysis of the data that represents the behaviour of each appliance after being switched on and off in order to add the singular features to our database. Thus, after a depth study of the results of the recorded data (Tab. 1 and Figure 2), the visible features of appliances will be presented and explained in this section. These one will be beneficial for the identification of appliances, because they will specify the profiles of various devices investigated what will refine the database for identification. Here are these notable features:

1) Two-phase loads

We noticed that the oven and the stove are supplied by two-phase electric power rather than a single-phase, which makes the task of identification easier. Nonetheless, we perceive that it becomes difficult to distinguish the stove burner No. 1 of the stove burner No. 4 as well as the stove burner No. 2 of the stove burner No. 3 given that their ΔP and ΔQ are clearly analogous. However, as regards the electric stove, we estimated that some flexibility, about the reliability of the identification of stove burners, would not be an issue for the activity recognition as long as we know that the stove operates with a negligible error rate.

Table 1. Loading features of household

ID	Name of appliance	Average active power (ON)	Average active power (OFF)	Average reactive power (ON)	Average reactive power (OFF)	Reactive power continuously (Y/N)
1	Stove burner No. 1	1005W 969W	-1000W -964W	774W -576W	-771W 577W	Y
2	Stove burner No. 2	524W 501W	-527W -508W	465W -284W	-463W 287W	Y
3	Stove burner No. 3	524W 464W	-527W -463W	517W -283W	-521W 276W	Y
4	Stove burner No. 4	1167W 1116 W	-1166W -1122W	857W -657 W	-857W 659W	Y
5	Electric kettle	1560W	-1553W	-403W	398W	N
6	Oven (bake mode)	1459W 1408W	-1456W -1399W	1030W -802W	-1023W 798W	Y
7	Toaster	873W	-869W	-178W	177W	N
8	Range hood fan (mode :high)	153W	-155W	388W	-389W	Y
9	Coffee maker	723W	-727W	Negligible	Negligible	N
10	Microwave	1045W	-1050W	Erratic	Erratic	-
11	Hair dryer (mode 1)	1719W	-1705W	-349W	341W	N
12	Hair dryer (mode 2)	759W	-749W	-181W	178W	N
13	Blender	417W	-247W + -182 W	-236W	212W	N
14	Electric mixer	435W	-235W + -207 W[1]	406W	-372W	N
15	Stereo	200W to 1150W	-150W to 1200W	Erratic	Erratic	Y
16	Refrigerator	1100 W	-1025W + -165W	1025W	-1025W	N

2) Power peak

Logically, the ΔP and ΔQ required for the operation of a device are the same that disappear when it is turned off such that the sum of the ΔP and ΔQ during the "on" event and those of the "off" event will cancel or leave negligible values due to fluctuations. However, we notice in Table 1 that some energy losses recorded occur in two stages. In fact, it arises because some devices undergo a rapid peak power at the switching on, i.e., the power of the line-to-neutral supplying the appliance experienced a sharp increase at the "on" event to decrease almost immediately before stabilizing at a value still greater than that the initial state prior to the turning on of the device.

Then, power off, it will have a second negative delta of power, which added to the first, is practically equal to the positive delta of the "on" event. This specification specific to devices having IDs 13, 14, 15 and 16 has been harnessed for the database in order to simplify their identification by the algorithm conceived for the activity recognition. Latter are recognizable in Table 1 by the fact that there is addition of P to the switching off, as the loss of energy takes place in two steps.

3) Overlapping of load signatures

By analysing carefully the Figure 3 that positions the appliances by their averages of the loading features, we notice that it contains several appliances from the Table 1 whose identity would be easy to confuse. For example, the devices No. 7 and No. 12 are likely to be confused if the identification of devices was based solely on the characteristics of P and Q.

Therefore, seeing appliances with similar particularities without features to make the distinction in Figure 3, we chose to plug them into electrical outlets supplied by different electric lines of a three-phase power system. This allows us to rank them assuming they are never moved into an outlet with a different power phase from that allocated to them.

4) Erratic features

For some cases where the features are irregular, we will have to create, in the database, as objects as they have different profiles. For example, for the microwave, the ΔQ do not follow the same trend for the various samples collected. However, most have quick changes of Q at the turning on and/or off (i.e.: it is not continuously). Nonetheless, in this case, the best solution is to create multiple objects adapted to their various pattern. It should be noted that in Table 1, only devices whose behaviours were generally observed have been put; there is no duplication of appliances. In addition, when we examine the values of features of the stereo, they do not appear to have a well-defined center. Hence, in the database, it will have features with broad ranges.

5.3 Experimental Procedure for the Phases 2 and 3

To validate the operation of our algorithm of activity recognition, first, we carried out 10 tests to evaluate the accuracy of the detection of the on/off events for individual appliances, except for the refrigerator (5 tests). Consequently, each appliance was turned on and off 10 consecutive times without involving any other devices.

Next, we simulated four scenarios that include activities of daily living. These scenarios were taken from the real case experiments made with patients with Alzheimer's disease within our laboratory [14]. Each scenario was repeated a total of 10 times to determine then the accuracy of detection and identification of events obtained through our algorithmic method for each of them. It is important to consider the fact that, unlike previous tests, scenarios may involve the operation of multiple devices at the same time i.e. up to 6 appliances.

- Scenario 1: Make tea and toasts.
- Scenario 2: Make coffee by drying the hair and make toasts.
- Scenario 3: Make coffee, pancakes while listening to music.
- Scenario 4: Make coffee, milkshakes, eggs, toast and bacon while listening to music.

5.4 Results and Analysis of the Results of Phases 2 and 3

The database, resulting from the analysis of the characteristics recorded for each appliance, has been integrated into our final algorithm for the activity recognition through the identification of devices in operation. Thus, for the second part of the experiment, the percentages of success for the identification of individual devices are shown in Figure 4.

We noted that in the case of individual appliances, most have rate identification events 100%. Devices with small failure rates are devices with IDs 8, 15 and 16. However, it was expected because of the following facts:

- The ΔP of the fan is usually very small, so difficult to detect in reason of the high threshold that was issued to counter the detection of fluctuations in the system.

- At the turning off of the stereo and the refrigerator, the ΔP is really small, so there are 2 possible cases, either the event is confused with a change and detected too soon or the value is so small that it is not detected.

Furthermore, when we proceed to the analysis of the results of our tests of four scenarios, we have reason to be satisfied. The percentage of successful event for the scenarios 1 and 2 is 100%.

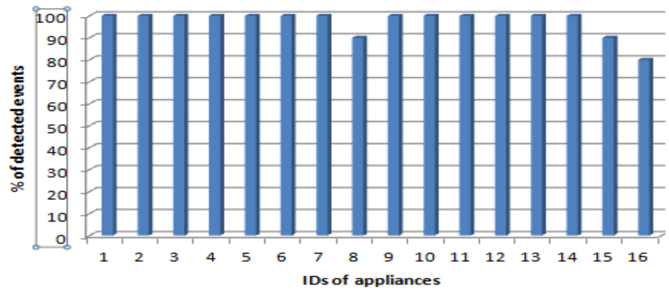

Figure 4: Results of events of individual appliances.

Then, for the scenario 3, 97% of the events have been detected and correctly identified and the remaining 3% corresponds to problems related to the detection of the fan and turning off the stereo as noted above. Thus, these sources of error were fairly predictable.

Finally, approximately 98.3 % of the on/off events have been correctly identified and all the misidentified events are associated to the detection of switching off of the stereo. Overall, our activity recognition algorithm demonstrates a high accuracy and outstanding effectiveness in recognizing devices, what is very satisfactory given the low investment and the basic hardware used.

6. COMPARISON OF OUR APPROACH

The comparison of our method with related works is complex. Table 2 aims to visually summarize this comparison. Actually, each team of researchers offered different methodologies, worked in various environments and had different goals. Nonetheless, compared to other approaches, ours requires less equipment and installation, since our system to acquire the data is centralized at a point and we can access it from an authorized computer. Indeed, unlike other methods [3, 5-7], we do not use sensors or other additional tools to read the power data. Sometimes, these last introduce some form of intrusiveness [3, 6]. Another criterion to consider is the feature amount that is used to define the load signatures, because, generally, it varied the hardware costs. For our part, we work with three loading features which allow us to recognize 16 appliances.

Nevertheless, in contrast with ways of process extracting the harmonic feature [2, 5, 11], the third did not generate any extra expenses, because, in fact, it consisted of using the existing electrical outlets according to their line-to-neutral to our advantage to reduce the possibilities of misidentifications. Also, once the feature extraction algorithm is programmed, the last of the tests to extract the features for each appliance is not really long in comparison with approaches which need to receive a classification training [11]-[12] even if they obtain an excellent precision the time of training depends of the amount (N) of appliances ($\approx 2^N$). Essentially, our developed pattern is attractive, because it has investment altogether minor, it manipulates few data, it is straightforward and especially it has excellent accuracy despite the restrictions associated with it.

Table 2. Summary table of different NIALM

Authors	Technique	Total of features	Material	Sample rate (Hz)	Accuracy (%) of identification	Total of identified devices/modes
Hart et al. 1992	Steady-state Punctual intrusion	2	General-purpose hardware Sensors	N/R	N/R	N/R
Drenker et al. 1999	Steady-state	2	Recorder Power meter	N/R	≈ 95 %	6
Laughman et al. 2003	Transient	3	Sensors Monitor	N/R	N/R	N/R
Bijker et al. 2009	Optimisation model	1	Power meter	N/R	≈ 51%	6
Liang et al. 2009	Steady-state LUR	3	Power disturbance analyzer Smart monitoring plugs	1 1.7×10^{-2}	≈ 92%	10
Liang et al. 2010	Steady-state Transient	8	Analyzer	1.536×10^{4}	≈ 92,7	32
Lin et al. 2010	Steady-state Transient Training	1	Control circuit	60	> 98.75	3
Rahimi et al. 2011	Steady-state Mahalanobis distance	2	Power bar Sensors Converter Voltage transformer Voltage divider MATLAB	1×10^{3}	100%	7
Our approach 2012	**Steady-Stade Euclidean distance**	**3**	**Smart power analyzer**	**60**	**≈ 98%**	**16**

7. CONCLUSION

In this paper, we presented an economical and efficient method for activity recognition within a smart home, which is based on the analysis of load signatures represented in a 3-D space and power analysis at the steady-state. As we pointed out, most existing recognition approaches in smart homes [15] rely on distributed sensors (RFID, electromagnetic, pressure mats, infrared, etc.), which are often expensive, heterogeneous and complex to install in old infrastructures. Also, they are intrusive and they need maintenance. Our system is also much simpler in terms of materials, because it requires only a single analyzer. Our proposal constitutes an original application and new algorithmic method. We implemented and rigorously tested this new approach by conducting an experiment in our smart home prototype by simulating daily scenarios taken from clinical trials previously done with Alzheimer patients. The promising results we obtained were presented and compared to other approaches, showing that, with an exceptionally minimal investment and the exploitation of relatively limited data, our method can efficiently recognize activities of daily living for providing assistive services

Although our results are promising, we consider that there are some limitations. For example, we have to find a suitable solution to resolve the restriction to plug the appliances, because for the moment the residents have to respect a particular schema of connection. Also, we need to test the algorithm in several real life environments.

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