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Learning User Activities from Energy Demand Profiles

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Abstract

In this paper, we propose the use of *energy load profiles* to learn human activities. An *energy load profile* determines the energy consumption of an appliance during a specific interval of time. We propose the use of clustering techniques to group the different profiles according to their temporal consumption. Both *Hard* and *Soft* clustering techniques are evaluated. We have tested the method with data from *REMODECE (Residential Monitoring to Decrease Energy Use and Carbon Emissions in Europe)*[1] database.

Keywords: Ambient Intelligence, Modelling human activities, Energy profiles, Clustering

1. Introduction

Ambient Assisted Living (AAL) is a new research area that appears by applying Ambient Intelligence to the field of elderly people assistance at home. AAL has emerge as one of the most supportive to monitor human activities to support different field areas, such as, e-health, assisted-living, entertainment, and most recently energy efficiency. Its aims are to increase elders' autonomy and their home staying. Among its issues, the modelling of the human activities is becoming more prominent.

In that regard, learning human activities requires the design of dynamic systems capable of learning different types of predefined activities in real time. Mainly, those systems are based on two main concepts: actions and behaviours (or activities). We define an *action* as an event that is done by users at a given place and time; whereas, a behaviour is a sequence of actions that is executed in a specific interval of time. A formal definition of those concepts can be found in [1].

In general, systems able to model activities are capable of learning the relevant "actions" or "elements" for a specific behaviour [1, 2, 3, 4], determining which elements should (or not) belong to the studied activities. To do that, they need information about the user activities in the environment. That process can be seen from different points of view, depending on the sensors' localizations and usages, named *wearable* sensors o *environmental* sensors. The former ones are more focused on users' atomic activities, attached to the users and able to gather any movement that they may perform. Traditionally, those methods are focused on learning and recognizing user's movements (e.g. walking, running, standing up, etc.) [5]. On the other hand, *environmental sensors* are capable of providing a vision of the whole scenario. These sensors are located in specific and prefixed points in the ambient, where users can interact with them without noticing. Those interactions are used by the algorithms to infer the user activities and support them. The most typical example of this kind of scenario is the Smart Environments, and more concretely, Smart Homes[6, 7].

Moreover, most of the previous approaches rely on expert information to understand the activities, either experts specify which actions should be studied or they specify the temporal period of time when the behaviour should be performed. Nevertheless, not always can we have this kind of information or, even if we have it, not always represents the users activities. General Activities are usually provided without users' own characteristics. On the other hand, in most cases, the installation of *Human Activities Systems* in a real scenario implies that the user have to invest some money in order to adapt the environment to the systems' requirements, for instance, installing pressure sensors in the chair to detect whether or not the user is sitting on it. Not all users are willing to incorporate to their homes devices (sensors, actuators) that can control each of their movements. Related to this drawback is the fact that the user environment cannot be changed. Systems modelling human activities are based on the Ambient Intelligence features: transparent (work unobtrusively, without users noticing the existence of devices in the environment) and ubiquitous (potentially, they can provide support any where at anytime).

New advances in the Energy field could help to overcome those drawbacks. Since the start of the Energy Efficiency Awareness, researchers have tried to accurately introduce the human factor within the models of energy loads. Some of them have put its emphasis precisely on modelling human activities since it could help in the prediction of energy requests services in housing, in order to avoid some problems like peak consumption. Several studies [8] confirm that users (and their associated behaviours) are a crucial factor in modelling energy demand (even more than the equipment itself, in some cases).

[1]http://remodece.isr.uc.pt

Energy load is quite influenced by different factors, such as, weather, building infrastructure, internal working equipment, etc. Nevertheless, none of those parameters influences the building energy demand as much as the user activities inside them [9]. For instance, the expected energy demand for a user when she is cooking cannot be the same that the needed when working out at home. The energy demand required in each case is completely different, not only because the devices they are using but also to maintain the user comfort. In the energy domain, it has been proved that it is not difficult to infer the behavioural patterns of the inhabitants of a house from their energy consumption data [10].

Currently, electric companies have mechanism to monitor the electricity consumption by users at home, and even further, some of them know which devices are the one consuming the electricity. New thermostats that learn when to switch on and which temperature to set are the most prominent example (Nest thermostat[2]). Energy consumption and energy demand can be represented as time series or a graphic curve representation. As expected, the consumption included in the profile will be higher when the appliances are used, what, in most cases, means that the user was interacting with them. Therefore, studying those profiles we can learn when the user is performing particular actions.

Based on this fact, we propose a method to model user activities at residence according to their energy profiles. The method assumes that, generally, a type of behaviour is composed by a sequence of actions that are daily executed at the *same interval of time*[1]. For example, if someone has to start working around 9:00 everyday, we could assume that she has breakfast around 8:00, using specific devices to prepare it, such as, toaster, coffee machine or kettle. The use of those appliances can be seen as actions (e.g. she turns on the toaster), events over the devices. Thus, we propose a method capable of grouping the *Energy profiles* regarding temporal coincidence. Our proposal uses the *Clustering* technique, to be precise, *k-means* and *Fuzzy k-means*, to groups the temporal similar *energy load profiles*, generalizing them as part of the same behaviour.

The remainder of this paper is organized as follows. In Section 2, a background of the relevant aspects of this paper is presented, in concrete, the main relevant aspects of *Modelling human activities*, *User activities impact on energy demand* and *Temporal Clustering* are explained. Section 3 shows the method to learn the user activities based on *Energy load profiles* in depth. The experimental results are shown in Section 4, and finally, Section 5 offers the conclusion.

[2]https://nest.com/

2. Background

In this section, we present a brief state of the art of the most relevant areas that we combine in this approach: modelling human activities, the impact of user activities on the energy demand and time series clustering.

2.1. Modelling human activities

Most projects in this area focus in attendance of elders or people with special needs at smart homes, and more specifically in the modelling, recognition, and prediction of human activities, as for instance the projects TigerPlace [6], Cogknow [7], and CASAS [11].

Previous works offer studies of a wide variety of aspects regarding human activities, ranging from the underlying sensor network for user data acquisition [12], to representation [3], behaviour modelling [4], temporal aspects [13] and applications [6]. Probabilistic and uncertainty models are the most common choice in the literature, such as probabilistic sequences of objects touched by the user [12], Learning Automata[1], Hidden Markov Models (HMMs) [3], Markov Decision Processes [14] or image feature extraction techniques combined with a Naive Bayes classifier to identify the human activities [15]. A complete taxonomy of recognizing human activities is proposed in [16].

However, most of these projects depends on the reliability of the sensors and actuators installed in the environment, and on the user acceptance of those devices. In this paper, we propose the use of an alternative source of information, *energy user profiles*, since those profiles can determine the user actions by detecting whether or not the user is using a specific appliance.

2.2. User activities impact on energy demand

Modelling user activities is an emerging research area, and even more, applied to the Energy field. In the last few years, both researchers and enterprises have agreed that understating user's energy consumption is key to control the energy consumption, above all, in those buildings where users could access easily to appliances [9]. In that way, a first approach for modelling user behaviour in the context of real energy is proposed in [17], focused on learning the window opening behaviour in residential buildings. The methodology is based on a medium/long-term monitoring, developing a probabilistic approach for modelling the human behaviour related to the control of indoor environment.

The user impact on energy consumption may be measured in different levels of granularity, always depending on the type of building and its use. Rollins et al. [18] made a first approach studying the influence of users in energy requirements at individual appliances level. Authors aimed at understanding how users consume energy by means of specific appliances, finding its schedules of usage. Similar studies have tried to understand the effect of domestic occupancy profiles on the energy performance of a house or industry[19].

In this paper, we will try to step forward studying the influence of user at appliances levels, in order to modelling the human behaviour and supporting the daily living routines.

2.3. Clustering of time data series

Clustering is the unsupervised classification of patterns (observations, data items, or feature vectors) into groups (clusters)[20]. Traditionally, clustering algorithms have been divided into partitioning and hierarchical algorithms. The former one divides the data in k clusters, with k as an input parameter of the algorithms, whereas the later divides the scope into regions, and each cluster is contained in one of that regions. Among its advantages, clustering techniques are considered as an unsupervised learning since do no require domain knowledge and labelled data. For this reason, clustering is quite useful for pattern-analysis, grouping, decision-making, and machine-learning situations, including data mining, document retrieval, image segmentation, and pattern classification [20].

Focusing on Time series, the clustering techniques aim to partition time series data into groups based on a similarity measure or distance, obtaining a cluster in which all the time series included in it are similar, finding the most homogeneous clusters that are as distinct as possible from other clusters. Various algorithms have been developed to cluster different types of time series data [21]. Some approaches work directly with raw time series data, called raw-data-based approach, while others converts a raw time series data either into a feature vector of lower dimension or a number of model parameters called feature-based and model-based approach.

3. Clustering energy demand profiles to identify User activities

In this section, we propose a clustering method to find common patterns among the user energy demand profiles. The basic idea is to partition the set of time series into a specific number of clusters according to the similarity measured. Each cluster will represent a type of behaviour: a set of actions that, performed during the same period of time, have a common objective. On the other hand, each time series in the cluster represents the action that the user is performing and when she should do it.

In previous approaches, we have followed the idea that we have a monitored environment, from which we can monitor the user during any of their movements [22]. In addition, we used expert knowledge

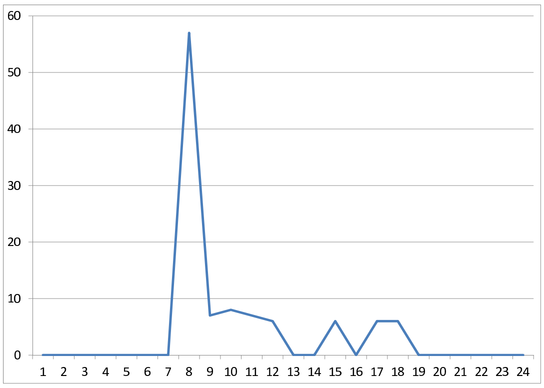

Figure 1: Example of a Daily load profile for a Kettle

to identify activity periods at home in order to study a specific piece of the Stream Data generated from the monitoring process [1, 13]. Even though these kind of assumptions are the most common in the AAL research field, we cannot always rely on having the expert knowledge or having a monitored house. In order to overcome these possible limitations, we propose a method that uses alternative information to determine whether or not an user is doing something at their home, concretely, *energy load profiles* of each appliance at home. Generally speaking, *Energy Load Profile* represents the electricity usage for appliances related to different building uses and typologies. They provide the information about when a specific device is used, for how long and the intensity of its use. An example of *energy load profiles* is shown in Figure 1, which represents the daily load profile for a Kettle. As can be seen, although the Kettle may be used during the whole day, it is used with more intensity and frequency from 07:00 to 09:00, what could be generalized as it being part of the *'having breakfast'* routine.

In general, profiles represent realistic detailed information, since they mean the end-users interaction with the energy equipment and consuming devices. Although the generation of the energy demand profiles is not always direct (as proven by the numerous studies about the profile generation process [19]), in this paper we assume that we have those profiles ready to be used in our system.

As a *Energy Load Profile* represents a temporal evolution of the electricity demand, we can represent them as time series. A time series is a sequence of real values collected at predefined intervals of time or prefixed time. We can represent a time series as an ordered set of n real values ($Y = y_1, y_2, ..., y_n$), where n is the length of Y, and y_i is the real valued number of Y at timestamp i.

We should remember that when two time series are compared they should be normally sampled at the same interval, and their length (or number of time points) be the same, if possible.

Once we have the Energy Load Profiles as time series, we are prepared to apply Time-Series clustering to them. We propose to use the well-known clustering method of *k-means* [20], although we plan to apply other clustering techniques in the near future.

k-means is based on the concept of the minimization of a fitness function, traditionally, defined as the distance between two elements, or in our case, two time series:

Definition 1 (K-means algorithm [21]). *Given n patterns $x_k|k = 1, ..., n$, k-means determine k clusters centers $v_i|i = 1, ..., k$, by minimizing the objective function given as*

$$\min J_i(U, V) = \sum_{i=1}^{k} \sum_{c=1}^{n} u_{ic} d(x_k, v_i) \qquad (1)$$

where $u_{ik} \in 0, 1 \forall i, k$, $\sum_{i=1,k} u_{ik} = 1 \forall k$, and $d(x, y)$ is the distance measure.

K-means assigns to every cluster a centroid. Each element will be included in the cluster whose centroid is more similar (computed by a similarity measure defined according to the problem's domain). In every iteration, the centroid is updated by taking into account the new elements included in the cluster.

The k-means algorithm is classified as *Hard clustering*: any profile X either is or is not part of a particular cluster. However, in our domain, some actions (profiles) may be part of different activities. For instance, turning television on and sitting on a chair could be part of both having breakfast and watching television. Therefore, we need a method capable of performing *Soft clustering* over the different profiles: a profile X might belong to more than one cluster, with associated membership values. The membership value will help to determine the strength of the association between the profile and the cluster.

To be precise, we propose the use of the fuzzy version of the *k-means* algorithm: *Fuzzy k-means* (FCM)[23].

Definition 2 (*Fuzzy k-means* algorithm [21]). *Given n patterns $x_k|k = 1, ..., n$, k-means determine k clusters centers $v_i|i = 1, ..., k$, by minimizing the objective function given as*

$$\min J_i(U, V) = \sum_{i=1}^{k} \sum_{c=1}^{n} (\mu_{ik})^2 d(x_k, v_i) \qquad (2)$$

where $u_{ik} \in 0, 1 \forall i, k$, $\sum_{i=1,k} u_{ik} = 1 \forall k$, and $d(x, y)$ is the distance measure.

Since similarity is fundamental to the definition of a cluster, a measure of the similarity between two time series has to be defined. Several methods, such as Dynamic time warping (DTW) or others, have been tested to select the most adequate similarity measure in our context. Finally, although the use of Euclidean Distance in the context of time series is controversial, we have selected to use it since it facilitates to compare two (time-dependent) sequences where the sequences has a linear (elastic) alignment. Using Euclidean distance, we can calculate which elements are used during the same interval of time through matching similar shapes of phase in the time axis. The Euclidean distance is computed as follows:

Definition 3 (Euclidean distance). *Let x_i and y_j be a P-dimensional vector of values. We compute the Euclidean distance as:*

$$d(x_i, y_j) = \sqrt{\sum_{K=1}^{P} (x_{ik} - y_{jk})^2} \qquad (3)$$

4. Experiment and Discussion

4.1. Experimental settings

To run our experiments, we use the *REMODECE (Residential Monitoring to Decrease Energy Use and Carbon Emissions in Europe)*[3] database. This database stores characterizations of residential electricity consumption by end-user and by country, including Central and Eastern European Countries.

Among other type of information, we can retrieve Daily average load curves for specific appliances and projects, collected in the REMODECE project. Those curves are divided into 24 hours, with one hour intervals. Every point in the profile represents the Power consumed by the appliances during that interval.

As example of the data used in the experiment, Figure 2 shows some Daily load profiles for a specific project, included in the REMODECE database, *Remodece Fr in France (2006-2008)* for some appliances. Notice that we have normalized the values of Power (Watts) in order to compare all the appliances in the same conditions.

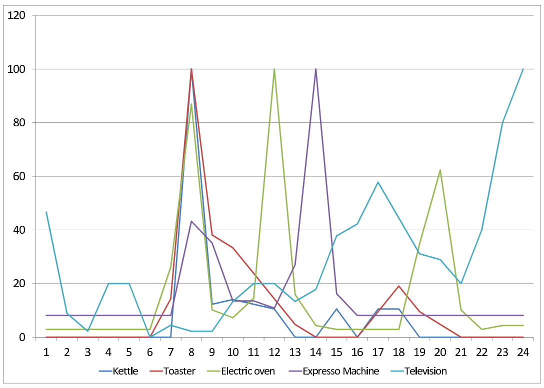

Figure 2: Daily average load curve for Remodece Fr in France (2006-2008) Project, for Having Breakfast

Although *REMODECE database* contains data from different projects and appliances, they are not

[3]http://remodece.isr.uc.pt

Project	Appliances
Remodece Fr	DVD Player, Television, Home Cinema, Laptop, Bread Maker,Kettle, Espresso Machine, Toaster, Dish Washer
Remodece Cz	Television, Laptop, Kettle, Espresso Machine, Toaster, Dish Washer, Microwave
Remodece It	DVD Player, Television, Home Cinema, Laptop, Bread Maker,Kettle, Espresso Machine, Toaster, Dish Washer, Microwave

Table 1: Appliances studied for each project during (2006-2008)

complete, since we can find combinations of those two elements that do not contain stored data. In order to compare correctly the results obtained, we have selected only those examples that we can consider complete: they have data for each appliance that we studied. The different combinations used in this test are collected in Table 1.

According to Remodece profiles and expert knowledge, three types of behaviour could be identified from data: To have breakfast (B_1), To watch television (B_2) and To wash the dishes (B_3).

In order to execute our experiments, we have used the matlab functions[4] *kmeans* and *fcm* used for *k-means* clustering and *FCM* clustering, respectively, to partition the profiles data into k clusters.

4.2. Results and discussion

Over this dataset, we have tested the performance of both *k-means* and *fuzzy k-means* algorithms. We have run the experiments for $k = 3$ (the number of behaviours that we expected to learn: To have breakfast (B_1), To watch television (B_2) and To wash the dishes (B_3). Table 2 summarizes the results for *k-means* and *Fuzzy k-means* for each used dataset. We organize the results for each behaviour, applied algorithm and number of clusters as percentages in four categories: True positives (TP) are positive profiles correctly labelled in the type of behaviour. False positives (FP) refer to negative profiles incorrectly labelled as part of the behaviour. True negatives (TN) correspond to negative profiles correctly labeled as non part of the behaviour. Finally, false negatives (FN) refer to positive profiles incorrectly labelled as non part of the behaviour.

As seen from Table 2, a 100% score in most of the positive and negative patterns was obtained, meaning that the profile where correctly classified by the system. In addition, we obtained a 0% of most of false positive and false negative patterns, what means that those profiles that should not belong to the behaviour are correctly categorized as non-part. Also, notice that, although we could assume that having less profiles could make easier the clustering process, we obtained good results with the *Remodece It dataset* composed by 10 different profiles. On the other hand, we would like to remark that the best results are obtained for the To have breakfast (B_1) behaviour. The reason of that fact is that its temporal execution is quite different from the rest, and it cannot happen in any moment of the day. This is a problem that may be solved combining the similarity measures.

Focusing on flexibility instead of accuracy, we can affirm that *FCM* provides better results than *k-means*, since *FCM* profiles can be included in different clusters. The coffee machine is an example of this situation. In the *Remodece It dataset*, using the *k-means* algorithm the coffee machine is excluded from the To have breakfast (B_1) (see score 75% from 2). However, using *FCM* that profile is included, although not with a 100% membership degree.

5. Conclusions

In this paper, we have proposed a method to group *Energy load profiles* in order to obtain the relevant actions of a specific type of behaviour. *Energy load profiles* provide information about the energy consumption of appliances during a period of time. This fact allows us to hypothesize that higher consumption means the user is using that appliance. We analysed that information, found relationships between different profiles (appliances, actions) and generalized them as particular behaviours. To achieve these objectives, we have proposed the use of time series clustering techniques, *k-means* and *Fuzzy k-means* with the Euclidean distance, and tested them.

In this domain, we have proved that *Fuzzy k-means* produces more flexible results when some actions belonging to different activities are expected. However, as anticipated, the *k-means* algorithm is more accurate because it is capable to distinguish between the true relevant actions and those that might be done during the performance of a behaviour, but are not main actions.

As future work, we aim to provide a complete semantic description to the Energy Load Profiles and extracted clusters (behaviours), together with a recognition system capable of identifying user actions in real time and provide support to perform them. As well, we would like to make users understand their own habits, routines, from the energy point of view, in order to raise user consciousness of the energy squander and suggest some changes in their behaviour that could help to manage and reduce the energy at home.

[4]Mathworks.http://www.mathworks.com

Dataset	Behaviour	Algorithm	% TP	% TN	% FP	% FN
Remode FR	To have breakfast (B_1)	*k-means*	100,00	100,00	0,00	0,00
		FCM	100,00	66,67	33,33	0,00
Remode FR	To watch television (B_2)	*k-means*	75,00	100,00	0,00	25,00
		FCM	100,00	100,00	0,00	0,00
Remode FR	To wash the dishes (B_3)	*k-means*	100,00	50,00	50,00	0,00
		FCM	100,00	66,70	33,30	0,00
Remodece Cz	To have breakfast (B_1)	*k-means*	75,00	100,00	0,00	25,00
		FCM	100,00	66,67	33,33	0,00
Remodece Cz	To watch television (B_2)	*k-means*	100,00	100,00	0,00	0,00
		FCM	100,00	100,00	0,00	0,00
Remodece Cz	To wash the dishes (B_3)	*k-means*	100,00	0,00	100,00	0,00
		FCM	100,00	100,00	0,00	0,00
Remodece It	To have breakfast (B_1)	*k-means*	75,00	50,00	50,00	25,00
		FCM	100,00	70,00	30,00	0,00
Remodece It	To watch television (B_2)	*k-means*	75,00	100,00	0,00	25,00
		FCM	100,00	90,00	10,00	0,00
Remodece It	To wash the dishes (B_3)	*k-means*	100,00	50,00	50,00	0,00
		FCM	100,00	70,00	30,00	0,00

Table 2: Accuracy of *k-means* and *FCM* for the studied behaviour

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