MACHINE LEARNING APPROACHES FOR ELECTRIC APPLIANCE CLASSIFICATION

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ABSTRACT

We report on the development of an innovative system which can automatically recognize home appliances based on their electric consumption profiles. The purpose of our system is to apply adequate rules to control electric appliance in order to save energy and money. The novelty of our approach is in the use of plug-based low-end sensors that measure the electric consumption at low frequency, typically every 10 seconds. Another novelty is the use of machine learning approaches to perform the classification of the appliances. In this paper, we present the system architecture, the data acquisition protocol and the evaluation framework. More details are also given on the feature extraction and classification models being used. The evaluation showed promising results with a correct rate of identification of 85%.

Index Terms—Signal processing, machine learning algorithms, power system analysis computing, energy consumption, energy efficiency, sustainable development

1. INTRODUCTION

Pushed by a growing trend of energy prices, by political objectives or by personal convictions, citizens are looking for solutions to reduce their environmental impacts. The energy bill due to house heating and use of electric appliance is an important area of progress in this domain. For example, recent studies have demonstrated that a continuous information feedback and fine-tuned automated management of the equipments in houses would allow for a reduction of the energy bill of 15% up to 30% [1, 2]. Such solutions, however, remain expensive and complex to configure.

Managing the electricity consumption in habitations and offices is a rather recent topic. The planned introduction of smart meters in our homes and the market availability for plug-based energy monitoring devices are pushing in this direction. Recent publications in the domain report on several mobile and web-based energy monitoring systems aiming at providing pertinent information to the user [3, 4]. With such system, the user needs to install monitoring systems on the plugs and to manually label the associated appliances. Finally, the user can visualize the consumption per appliance category and may perform optimization by activating or programming control rules. For example, a rule could be to switch on all charging appliances during night time when the electricity is cheaper.

Within this project, we propose an innovative system which can automatically recognize home appliances based on their electric consumption profiles. The installation of energy monitoring systems would then be much easier. Furthermore, control rules could be automatically proposed to the user by knowing the type of appliances. The technology could also find other applications such as the detection of defects, the localization of appliances in offices or hospitals, or the recognition of abnormal use of appliances (intrusion detection or elderly surveillance).

A specificity of our development is also to use hardware and software solutions that are as economic as possible, not only in terms of their costs but also in terms of their energy consumption. This specificity directed us to use low-end smart outlets called PLOGGs for measuring electric consumption signals [5]. Such devices measure diverse parameters of the electricity consumption every few seconds and are able to communicate it to a small-footprint mini-pc for processing.

In this paper, we show that machine learning techniques can be used to perform appliance recognition. Such techniques are very useful in this context thanks to their capability to learn models from data and to generalize the recognition on unseen appliances. Beside the software and hardware integration, a challenging part of the project was the settling of a data acquisition protocol that allowed us to tune and to benchmark the performances of the algorithms. As very few work have been developed in this area, another challenge was to develop meaningful and performant feature extraction on top of which the machine learning algorithms could be developed.

This paper is organized as follows. Section 2 gives an overview of the related work. Section 3 gives a description of our system. Section 4 gives details about the data acquisition protocol and campaign. In section 5, we describe the k-NN and GMM algorithms we used to perform the appliance recognition. Finally, in section 6, we present and discuss the preliminary results.

2. RELATED WORK

In the domain of electric signal analysis and appliance recognition, we can distinguish between two approaches according to the frequency of the energy measurements.

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The first approach, that we can qualify as *high frequency*, is based on the analysis of transient signatures appearing when appliances are, typically, switched on or off. Expensive high-sampling frequency sensors are requested and problems of sensitivity to the noise of other appliances are usually reported. The second approach, called here *low-frequency*, is based on the analysis of the short to medium term evolution of the electricity consumption, from few seconds to few minutes. This approach is based on the use of rather inexpensive sensors working at a low-sampling frequency, typically working around 1 Hz. Another way to categorize the related works is to consider the location of the sensors. Some approaches are based on *smart-meters* located at the entry point of the house and measuring the overall electricity consumption. Appliance recognition at the smart-meter generally suffers of imprecision due to the inherent problem of summation of consumption signals of the different appliances. Other approaches are using inexpensive *smart-outlets* potentially integrated in each plugs in the house and able to communicate their measurements remotely. An example of such smart outlet is given in Fig. 1. Intermediary approaches do exist where the sensors are located in between the smart-meters and the plugs, for example at the electrical distribution board. Our work is positioned in the domain of *low-frequency* electric signal analysis using *smart-outlets*, where very few work as yet been reported for the task of automatic appliance recognition.

According to this classification, some related projects can still be referenced. Ruzzelli *et al.* elaborated a system called RECAP (RECognition of electrical Appliances and Profiling in real-time), which uses a single sensor attached to the smart-meter to recognize appliances with artificial neural networks [6]. Lee, Lin *et al.* used a Bayes filter approach to recognize the state of use of appliances by monitoring the circuit-level electrical consumption from the distribution board in a house [7, 8]. Lee, Fung *et al.* observed and analyzed appliance signatures in various operating modes [9]. Leeb *et al.* developed a system identifying the operation of individual loads using transient patterns observed in the voltage waveform measured at an electric service outlet [10]. Patel *et al.* used a single sensor able to detect some electrical events generated by the abrupt switching of some appliances or the noise created by others while running. Then they applied machine learning techniques on those electrical events to recognize various appliances. [11]. Durand *et al.* developed a method based on hidden Markov chains for modeling and analyzing electric consumption curves [12]. Marceau and Zmeurneau elaborated a computer program for non-intrusive disaggregation of the total electricity consumption of a house [13].

3. SYSTEM DESCRIPTION

In this section, we give a description of the architecture of our system and we present the appliance recognition module. More details of the recognition algorithms are given in section 5.

3.1. Global architecture

Our system is based on a network of PLOGGs [5]. A PLOGG sensor is able to record a vector of electrical parameters related to the appliance being monitored. A low consuming computer (so-called here Green-PC) is then responsible to collect the acquired data from the PLOGGs and to store them into a relational database. The communication between PLOGGs and the computer is based on ZigBee and, in our case, using a Telegesis ZigBee USB dongle (see Fig. 1). Among existing wireless technologies, ZigBee is the cheapest and lowest consuming solution (e.g. compared to Wifi and Bluetooth). In future work, we plan for using e.g. carrier currents to transport data from the electrical outlets to the central *Green-PC*. The global cost of our system (without the PC) is about 150$ (i.e. about 100$ for a PLOGG sensor, 50$ for a ZigBee USB dongle).

Fig. 1. A PLOGG acquisition device and the communication ZigBee USB dongle

The architecture is illustrated in Fig. 2. The *Green-PC* provides a set of RESTful resources exposed as services that can be consumed by any types of clients, such as a standard web page or smart-phone application. Examples of features offered by these services are the data exploration and mining which allow the residents to understand the electrical consumption in their house. This kind of feedback potentially leads residents to change their behavior concerning the energy use.

3.2. Appliance recognition module

The appliance recognition module is based on supervised machine learning techniques. The purpose of this module is to recognize the type of appliance (e.g. a laptop, a coffee machine, etc.). For each appliance class, a stochastic model is built from the observed consumption profiles of several instances of this class. The overall set of data used to build the models is called the training set. Once the training is performed, the recognition module can be used to generate an hypothesis of the most probable appliance category from unseen data. In this work, we have at-

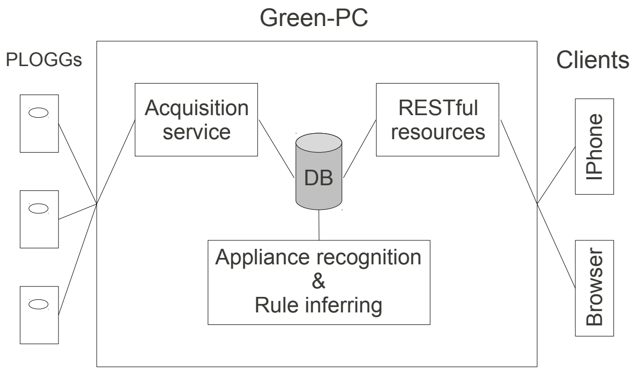

Fig. 2. The software architecture of our Green-PC

tempted to provide initial answers to three scientific questions that were raised in the elaboration of such recognition modules. A first question is related to the acquisition length of the electricity measurements, i.e. after how many seconds or minutes can the system emit a recognition hypothesis with fair performances. A second question is related to the feature extraction and modeling algorithms, i.e. what kind of features should we extract and what kind of modeling should we use. The third question is related to the evaluation procedure, i.e. how should we evaluate the performances of such systems.

4. DATA ACQUISITION

4.1. Campaign and protocol

To evaluate our recognition algorithm, an acquisition campaign was done under certain conditions and protocols. Because a real-time classification is not necessary for our system and, as starting point of our investigations, we performed numerous acquisitions for different appliance categories for a duration of 1 hour per acquisition. Such long acquisition duration allows to obtain a global view of the consumption profile for appliances which often consist of several operating states, e.g. standby, running, etc. Five categories (classes) of electrical appliances were taken into consideration: laptop, computer & monitor, phone charger, coffee machine and fridge/freezer. For each class, six different devices (different brands and models) have been recorded for a total of 30 acquisitions. The sensors were configured to provide observation values with a sampling frequency of 10^{-1} Hz (i.e. one acquisition every 10 seconds). Each observation value is actually a 4 dimensional vector of electrical parameters including the real power (W), the reactive power (var), the RMS current (A) and the phase of voltage relative to current (φ). Fig. 3 shows an example of the active power consumption measured for an appliance of class “laptop”. Note that the reactive power, as well as the phase of voltage relative to current, are useful to track appliances which contain inductance and/or capacitance components, such as a fridge. We took care that acquisitions were performed under realistic conditions (i.e. when the appliances were actually used). Finally, we chose to consider only non-overlapping signals. Thus, only one appliance is acquired at a time (i.e. only one single electrical device per smart outlet).

4.2. Dataset

An XML data structure has been designed for storing the raw observations, some meta-data and the ground truth values of the appliance categories. The format consists of the following parts. The header part covers the description of the dataset, the acquisition campaign, the author who did the acquisition, the acquisition place, the sensor device used, and the electrical parameters recorded. The body part contains the signal values with timestamps for all the electrical parameters.

5. APPLIANCE RECOGNITION ALGORITHMS

The algorithms used for the appliance classification were elaborated according to the process schematized in Fig. 4 and described in the following subsections.

5.1. Pre-processing

In our acquisitions, we realized that some acquisition values were lost or not sent by the sensors. This sometimes makes holes to appear in the sequence of acquired data. To recover an uniform sampling of $10^{-}1$ Hz, we performed a linear interpolation on the raw signal.

5.2. Feature Extraction

Features are extracted from both temporal and frequency domains. Each feature is “globally” computed. In other words, it is extracted on the whole signal (i.e. without using a sliding window) and separately for the four electrical parameters. In the temporal domain, the following features are extracted: minimum, maximum, mean, median and standard deviation. A Fast Fourier Transform (FFT) is computed to deal with features in the frequency domain. After the transformation, a filter bank is applied in order to partition the frequency spectrum into several banks representing each a limited range of frequency components. Each bank is implemented as a tent function from which the average output magnitudes are extracted. Empirically, we observed that using 20 filters in the bank (i.e. 20 extracted features) with an overlapping ratio of 20% lead to good performances. The motivation of this approach was to complete the temporal features with frequency based features able to characterize recurrent events like, for example, the periodic activation of a fridge compressor.

5.3. Splitting

The whole dataset is split into two disjoint sets, the training and testing sets by randomly selecting, respectively, 5 and 1 acquisitions per device class. A jack-knife procedure is also applied to generate all the different combination of training and testing sets in order to smooth the evaluation results. Note that the next steps described below (i.e. post-processing, training and classification) are

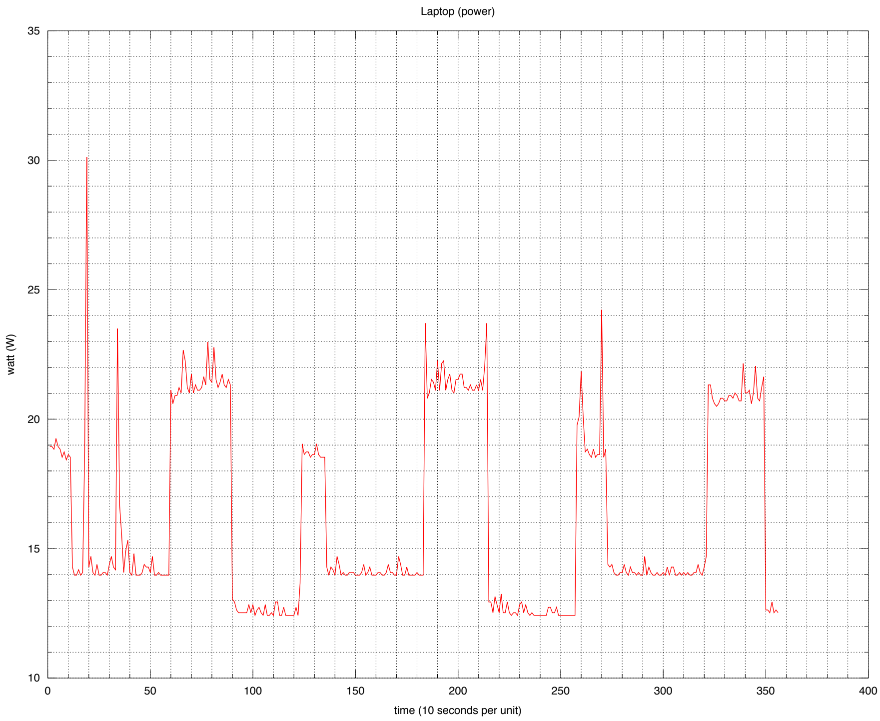

Fig. 3. Example of the active power consumption measured for an appliance of class "laptop"

logically recomputed for each combination of the splitting algorithm.

5.4. Post-processing

At the beginning of this step, a min-max normalization filter is applied to all feature vectors. All components (i.e. dimensions) of the vectors are scaled between 0 and 1. Thus, all features will have the same weight, which will prevent potential bias that some distance-based classification algorithms could typically introduce. A PCA is then applied to compress and remove the potential correlations between the features. The eigenvectors with their corresponding eigenvalue are computed by an eigendecomposition of the covariance matrix which characterizes linear interactions of feature vectors of the training set. Then the transformation matrix which contains selected eigenvectors is used to transform to the new coordinate system feature vectors of both the training and testing set. In this procedure, we skip dimensions which contribute for less than 1% of the variance.

5.5. Training & Classification

We used here two classification algorithms belonging to two different families. The first one is the k-Nearest Neighbors (k-NN) algorithm, which is one of the most trivial distance-based algorithm for classification. We started with k-NN because it is a good basis for performance comparisons with more advanced approaches like GMMs. This algorithm is based on the computation of the k nearest training vectors in the overall training set and to the election of the class through majority voting on the labels of the nearest vectors. In our case, we have defined the number of neighbors to 3 and used the Euclidean distance to compute the neighbors.

The second algorithm is based on a Bayesian approach where stochastic models are used to compute the likelihood of the feature vectors for each class. In our case, we used Gaussian Mixture Models (GMMs) that are modeled as a a weighted sum of multivariate normal distributions. Thus, for a particular feature vector $\mathbf{X}$, the probability conditioned on class ω_k is defined as:

$$p(\mathbf{x}|\omega_k) = \sum_{c=1}^{C} \alpha_c \phi(\mathbf{x}|\mu_{\mathbf{c}}, \Sigma_c),$$

where α_c is the weight of the component (i.e. Gaussian) c, under the constraint that $\sum_{c=1}^{C} \alpha_c = 1$ and ϕ is the PDF for the multivariate normal distribution.

A classical iterative Expectation-Maximization algorithm (EM) can be used to train the parameters of the GMMs, i.e. mean vectors, covariance matrix and weighting coefficients [14].

6. RESULTS AND EVALUATION

For our evaluation, 5 instances of each class have been used to train the model and the remaining instances composed the testing set. The recognition algorithm was then applied on all possible combinations of the training set and the testing set in order to smooth out the evaluation

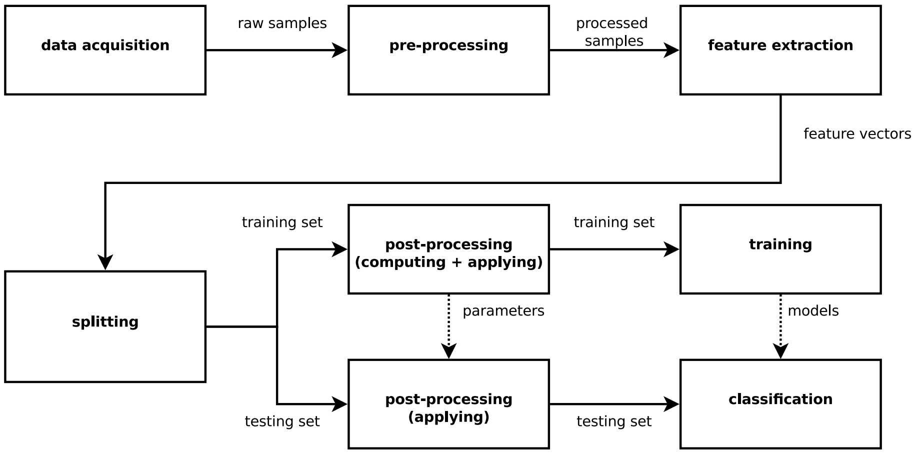

Fig. 4. The machine learning process

results. The k-NN algorithm leads to a promising performance of 85% correct recognition rage. Interestingly, the GMM approach did not lead to better performance. During our experiments, we made vary different parameters of the EM training procedure without being able to go above 85% correct recognition rate. This result was even obtained with a de-generated GMM with only 1 mixture in the model. The fact that the classification accuracy was not better with the GMM is probably due to the small quantity of data available to train the models.

An analysis of the confusion matrices was performed with some interesting observations. Sometimes a laptop was misclassified as computer & monitor and vice-versa, probably due to the fact that these 2 classes are relatively close. The same observation was done between the classes laptop and phone charger that were the most difficult to separate.

7. CONCLUSION

In this paper, we reported on the development of an innovative system able to automatically recognize home appliances based on their electric consumption profiles measured at low frequency with low-end sensors available on the market. The system is based on a typical machine learning approach were appliance models are learned from a set of training data. While our results would need to be validated on larger quantity of data, the initial performance are promising with a correct rate of identification of 85% measured on a task of 5 classes. In the elaboration of the system, we observed the benefits of performing a linear interpolation of the raw observations, of computing both temporal and frequency domain features and of performing a PCA on the features. Thanks to this feature extraction, a simple k-NN classification algorithm could be applied with good evaluation performance. Probably due to the low quantity of training data, the application of more complex modeling approaches based on GMMs did not lead to a significant improvement of the performance.

As future work, we plan to enlarge our database with more acquisitions and classes in order to go further in our experimentations and make our modeling more robust and accurate. We will also start to investigate how we can track different operating states of appliances using, for example, state-based modeling such as HMMs.

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