Appliance Recognition Using Power State Segregation at Low Sampling Rate

Fernando PANJAITAN[1] Eric Matsumoto OKAWA[1] Hitoshi KAKUTA[1] Johan HJELM[2] Toshikane ODA[2]
Shunsuke SARUWATARI[1] Hiroyuki MORIKAWA[1]

RCAST, The University of Tokyo[1] Ericsson Research Japan[2]

1 Introduction

The recent upsurge of concern for energy-efficiency has paved the road for research in context-aware power management systems. In contrast to existing fine-grained high rate appliance recognition algorithms, this research proposes a course-grained algorithm using off-the-shelf low sampling rate technology that can be easily installed in home/office environments.

2 Low Sampling Rate Appliance Recognition

We envision to conceive a context-aware power management system using low-sampling rate appliance recognition method. While a person's behavior can be determined by which and how electric appliances are used, which can be inferred from their power states transition, the location of the appliances are determined by monitoring which outlet was used at any given time.

Our system architecture is designed to collect appliance-level power consumption data to be used in automatic appliance identification processes. In order to simplify installation efforts, data is sent wirelessly (IEEE 802.15.4) to a sink node, which in turn forwards the data to a base station. Once enough data is collected, the electric characteristics of the appliances are calculated and saved into a database so that they can later be used to identify the same devices when plugged into an outlet.

In order to have a system that run continuously and perennially smaller data-sets are much preferable as they guarantee timely transmission and save energy on the nodes. Furthermore, sampling data sparsely allows for reliable wireless transmission and significantly reduces the amount of data to be processed allowing the system to handle a large number of appliances concurrently.

3 Proposed Algorithm

The proposed appliances identification method can be divided into two independent steps: states identification, and appliance recognition. The state identification step is the preparation phase where the appliances' electric characteristics are profiled and stored in a database. During this step, electric appliances are kept plugged into an outlet for an extended period of time so that all of their operating modes are isolated, their electric characteristics are calculated and stored in a database. In the appliance recognition step, the devices connected to the power line are compared against the list of devices created during the states identification step to determine if they belong to a particular state of a pre-registered device.

States identification step One big challenge in profiling electric appliances based on their load consumption information is to be able to segregate their multitude of operating states characterized by their distinct power features. For example, some appliances change their modes in a cycle (ex. the electric kettle in Fig.1) while others abruptly increase their power level before settling down into a new state (ex. humidifier in Fig.2).

In order to automatically identify the operating states of electric appliances, we apply the Density-Based Spatial Clustering of Applications with Noise algorithm (DBSCAN) [1] on their power consumption data. DBSCAN's ability to properly identify the states depends on the appropriate selection of the chosen inputs minPts and ϵ. For example, a one-watt change in a five-watt signal indicates a state change while the same one-watt change might just represent noise in a 120-watt signal.

In order to resolve this issue, we devised an algorithm that determines the value of ϵ dynamically according to the amplitude of the input signal. We define the value of ϵ to be proportional to the maximum value in the sampled data after transient spikes are excluded. Transient signals need to be excluded from the original signal since they can lead to an erroneous reading of the maximum value which is used to calculate the value of ϵ. We identify transient spikes by detecting sudden rises followed by a sudden drops within a predefined number of sample points and eliminate them by replacing with the mean of the data points before and after the spike. Since ϵ is now proportional to the maximum value in the data set, the enhanced DBSCAN only reacts to big changes in the input signal (when comparing to the amplitude of the signal itself) resulting in a high-accuracy clustering algorithm.

After we identify the states, we separate the data within each cluster and calculate their mean and standard deviation creating a two-dimensional vector which we call *reference vector*. Once the *reference vector* of the appliance is stored in the database, the device can be identified when plugged into any outlet.

Recognition step When an appliance is plugged into an outlet, the base station starts collecting and analyzing the input signal to check if it has been profiled before. After the base station samples a predetermined number of data points, it takes the acquired data set and calculates its mean and standard deviation.

From the calculated data, the base station creates a two-dimensional vector called *sample vector*. The Nearest Neighbor algorithm is then calculated between the *sample vector* and the *reference vector* to check whether the appliance falls within an euclidean distance from a known appliance. If the input signal fails to be identified, the base station adds the new device to its database.

4 Initial Evaluation

We evaluated the effectiveness of our method by determining the accuracy of the clustering algorithm when detecting different states, and the rate at which appliances are correctly recognized.

In our experiment, twenty appliances commonly found in home/office environment were analyzed for three hours each and our algorithm was successful in autonomously identifying all 44 of their operating states.

The detection rate of the appliances was determined by acquiring the load consumption data of each appliance for 20 seconds before calculating the *sample vector*. The detection rate of each appliance is shown in Table 1. On average, our method was able to recognize these appliances with about 90% accuracy. Recognition errors occurred mostly when appliances had similar power levels and near-zero standard deviations. This result was to be expected since the instantaneous load consumption was the only parameter that could be analyzed.

In addition, lower sampling rate yielded a longer detection time. Our system required 20 seconds to reach 90% accuracy when identifying a device while previous works using a higher-sampling-rate were able to recognize appliances in less than a second.

5 Conclusion

In this work, we proposed and implemented a recognition method for appliances and their operating states with a low-rate automated states segregation algorithm.

References

[1] Ester, M., Kriegel, H., Sander, J., Xu, X., "A density-based algorithm for discovering clusters in large spatial databases with noise," Proceedings of the Second International Conference on Knowledge Discovery and Data Mining , 1996.

Table 1: Recognition Results

Refrigerator (95%)	Plasma display (100%)	Mobile VPN (80%)
TV (90%)	Humidifier (100%)	Hairdryer (100%)
Playstation 3 (90%)	Stereo system (100%)	Ipod charger (75%)
Electric kettle(60%)	Iron (100%)	Digital photo frame (100%)
Laptop PC (70%)	Vacuum cleaner (100%)	Printer (100%)
Desktop PC (80%)	Access point (75%)	Wireless hub (100%)
PC Display(95%)	Desk lamp (100%)	

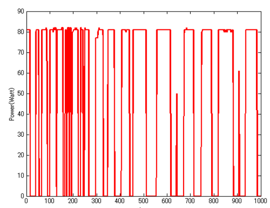

Fig. 1: Electric kettle

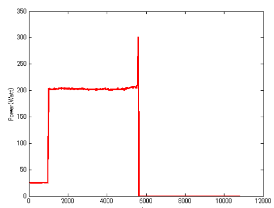

Fig. 2: Humidifier