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Usage Monitoring of Electrical Devices in a Smart Home

Saba Rahimi, *Student Member, IEEE*, Adrian D. C. Chan, *Senior Member, IEEE*, and Rafik A. Goubran, *Senior Member, IEEE*

***Abstract*—Profiling the usage of electrical devices within a smart home can be used as a method for determining an occupant's activities of daily living. A nonintrusive load monitoring system monitors the electrical consumption at a single electrical source (e.g., main electric utility service entry) and the operating schedules of individual devices are determined by disaggregating the composite electrical consumption waveforms. An electrical device's load signature plays a key role in nonintrusive load monitoring systems. A load signature is the unique electrical behaviour of an individual device when it is in operation. This paper proposes a feature-based model, using the real power and reactive power as features for describing the load signatures of individual devices. Experimental results for single device recognition for 7 devices show that the proposed approach can achieve 100% classification accuracy with discriminant analysis using Mahalanobis distances.**

Keywords-activities of daily living; nonintrusive load monitoring system; pattern recognition; smart home technology

I. Introduction

The increasing proportion of older adults makes it an essential task for today's societies to improve the daily living standards for the ageing population. One way to provide them with more health care options is developing smart technologies that support independent living. A home-based automated system can provide an environment that monitors the activities of daily living that can be used to predict the householder's health and well-being [1]. Various sensing, monitoring, and actuating systems are expected to play key roles in smart homes. To facilitate the monitoring of activities of daily living, we propose the use of a nonintrusive load monitoring system (NILM), which can be used to identify the operating schedule of various electrical devices within a smart home.

A NILM system is able to detect the operating schedule of various electrical devices within a smart home, such as when the devices are turned "on" or "off", and the period of operation for each device. There are certain devices that can be associated with predicting activities of daily living of occupants of a smart home (e.g., toaster, microwave, dishwasher, electric kettle, television, lamps). Determining the operating schedule of individual electrical devices belonging to this category will make it possible to monitor the activities of daily livings of residents. The NILM system is expected to be used in conjunction with other non-obtrusive monitoring sensor systems to enable robust and comprehensive monitoring within a smart home (e.g., RFIDs, thermistors, and pressure sensitive mats) [1].

A simple method of detecting the usage of electrical devices is to install separate sensors for each device; however, this method requires a large amount of sensors, and the installation and maintenance of these parallel meters will cause disruptions at the monitored site [2]. On the other hand, NILM systems [3-5] are able to detect the status of loads by analyzing the current and voltage waveforms that are recorded by sensors installed a common electrical point (e.g., main electrical panel). NILM systems identify individual electrical devices through their load signatures; load signatures are the electrical behavior of a device during operation, which differs from device to device. A load disaggregation method is used to discern individual devices within the composite load signal [6]; the composite load signal refers to the net behavior of more than one device operating simultaneously. In general, the process of load monitoring by NILM systems can be broken down into three main steps [7]: 1) device profiling, 2) event detection, and 3) pattern recognition. In the device profiling step, current and voltage waveforms are captured and features are extracted from the waveforms. Changes in the features are flagged as events during the event detection step. Pattern recognition uses a trained classification algorithm to map events to electrical devices and their operation state (e.g., "on" or "off").

Devices can be distinguished by their load signatures during transient changes or during their steady-state operation, or some combination of the two. In this work, we investigate features that can be extracted from the current and voltage waveforms during steady-state operation. Experimental testing of a NILM system is performed using 7 common household devices.

II. Methods

A. Experimental Setup

A NILM system (Fig. 1) was constructed to monitor various electrical devices connected to a common power bar. The current and voltage waveforms were measured at the input of the power bar.

Current measurements were obtained using split-core AC current sensors (Magnelab, Longmont CO, USA; models SCT-0400-005, SCT-0400-010, and SCT-0400-020) applied

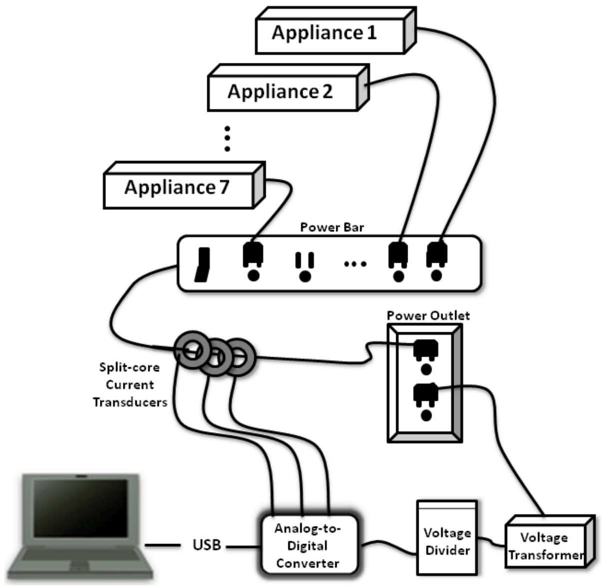

Fig. 1. Experimental setup for the NILM system.

to the live electrical wire feeding the power bar, simulating the monitoring at single, common electrical point. Split-core current transducers are easily installed by clamping them around wire. Simultaneously, split-core current transducers do not disrupt the continuity of the electrical system maintaining the safety of the electrical system. The Magnelab split-core current transducers output a voltage (maximum 0.333 VAC) that is linearly proportional to the current. Three split-core current transducers, each with a different maximum current rating, were used to enable accurate monitoring over a large current range (the transducer with the highest sensitivity that has not reached its maximum rating was automatically selected for the current measurement).

A voltage transformer was used to step down the 120 VAC voltage waveform to a 10 VAC output. A voltage divider circuit was used to further step down the voltage waveform to a range comparable to the output of the current transducer. Current and voltage measurements were digitized using a 12-bit analog-to-digital converter at a sampling rate of 1 kHz (National Instruments, Austin TX, USA, model USB-6008). Data were stored on a computer and processed offline using MATLAB.

TABLE I. ELECTRICAL DEVICES USED IN EXPERIMENTAL SETUP, ALONG WITH THEIR MEAN REAL POWER AND REACTIVE POWER (± STANDARD DEVIATION), COMPUTED ACROSS ALL ANALYSIS WINDOWS.

Load	Devices	Real Power (Watt)	Reactive Power (VAR)
1	Microwave	802.1 ± 21.81	214.14 ± 8.08
2	Electric kettle	785.66 ± 5.82	84.59 ± 1.19
3	Coffee maker	602.02 ± 4.57	65.56 ± 0.92
4	Laptop charger	65.95 ± 0.64	84.69 ± 2.01
5	Incandescent lamp	58.44 ± 0.39	9.09 ± 0.12
6	Computer LCD monitor	28.71 ± 0.38	36.04 ± 0.51
7	Fluorescent lamp	18.47 ± 1.44	26 ± 2.81

B. *Data Acquisition*

Seven household electrical devices (Table I) were used as loads in this study. To establish load signatures, each device was operated mutually exclusive of one another (i.e., electrical devices were not operated simultaneously). In this work, we consider electrical devices in one of two states (i.e., "on" and "off"). Multi-state electrical devices (e.g., microwave had different power levels) were used in only one of their operational states. Data were collected for from each device in its "on" state for 10 trials, with each measurement lasting 5 seconds. Data were collected during its steady state operation; that is, data collection commenced after the device under test was turned "on". A total of 70 measurements were completed (7 devices × 10 trials).

C. *Feature Extraction*

Each 5-second measurement was broken down into non-overlapping 100 ms analysis windows (50 analysis windows per measurement, as partial windows were discarded). The real power value was computed from the current and voltage measurements in each analysis window. Real power provides one of the most complete sets of information to explain load characteristics; however, electrical devices may have similar real power levels, making them difficult to discern using real power alone.

Device loads can be resistive, inductive, or capacitive. If the load is purely resistive, then the current and voltage signals are in phase. On the other hand, if the load consists of capacitive and/or inductive elements, it will affect the phase difference between current and voltage signals. In particular, for capacitive loads, the voltage is delayed with respect to the current while the contrary happens for inductive loads [8]. In addition to the real power, the reactive power is also computed as a feature from each analysis window to establish the steady-state load signatures; the reactive power is the power associated with capacitive and inductive elements.

D. *Pattern Classification*

Pattern classification was performed using discriminant analysis using Mahalanobis distances [9]. Classifier training was performed using 1 trial and classifier testing was performed using the remaining 9 trials. Cross-validation was performed by repeating the training and testing 10 times, such that each trial was used for training. There were a total

TABLE II. CLASSIFICATION CONFUSION MATRIX FOR REAL POWER. MEAN CLASSIFICATION ACCURACY 88.22%.

		Predicted load						
		Load 1	Load 2	Load 3	Load 4	Load 5	Load 6	Load 7
Actual load	Load 1	**3604**	896	0	0	0	0	0
	Load 2	2704	**1796**	0	0	0	0	0
	Load 3	0	0	**4500**	0	0	0	0
	Load 4	0	0	0	**4500**	0	0	0
	Load 5	0	0	0	111	**4389**	0	0
	Load 6	0	0	0	0	0	**4500**	0
	Load 7	0	0	0	0	0	0	**4500**

TABLE III. CLASSIFICATION CONFUSION MATRIX FOR REACTIVE POWER. MEAN CLASSIFICATION ACCURACY 85.79%.

		Predicted load						
		Load 1	Load 2	Load 3	Load 4	Load 5	Load 6	Load 7
Actual load	Load 1	**4500**	0	0	0	0	0	0
	Load 2	0	**2269**	0	2231	0	0	0
	Load 3	0	0	**4500**	0	0	0	0
	Load 4	0	1786	0	**2714**	0	0	0
	Load 5	0	0	0	0	**4500**	0	0
	Load 6	0	0	0	0	0	**4041**	459
	Load 7	0	0	0	0	0	0	**4500**

TABLE IV. CLASSIFICATION CONFUSION MATRIX FOR REAL POWER AND REACTIVE POWER. MEAN CLASSIFICATION ACCURACY 100%.

		Predicted load						
		Load 1	Load 2	Load 3	Load 4	Load 5	Load 6	Load 7
Actual load	Load 1	**4500**	0	0	0	0	0	0
	Load 2	0	**4500**	0	0	0	0	0
	Load 3	0	0	**4500**	0	0	0	0
	Load 4	0	0	0	**4500**	0	0	0
	Load 5	0	0	0	0	**4500**	0	0
	Load 6	0	0	0	0	0	**4500**	0
	Load 7	0	0	0	0	0	0	**4500**

of 31,500 test cases (10 repetitions × 9 test trials × 50 analysis windows × 7 devices).

III. RESULTS

Table I lists the mean real power and reactive power for all the electrical devices (± one standard deviation). Table II and Table III show the classification confusion matrices for the real power and reactive power, respectively. The mean classification accuracies were 88.22% and 85.79% for real power and reactive power, respectively. When using the real power and reactive power, simultaneously, the classification accuracy increases to 100%; the associated confusion matrix is shown in Table IV.

IV. DISCUSSION

High classification accuracy (88.22%) is achieved using the real power. This is not unexpected given the high repeatability of the real power measurements, indicated by the low standard deviation values in Table I. Table II indicates that load 1 (microwave) and load 2 (electric kettle) are the electrical devices that are misclassified most frequently; these devices were misclassified as each other and have comparable real power values, as well as the highest standard deviation values (Table I).

Electrical devices that have similar real power values may still be discernable through the reactive power. Using just the reactive power, a classification accuracy of 85.79% was achieved. Classification accuracy is lower than real power. Table III indicates that the majority of the misclassifications are load 2 (electric kettle) and load 4 (laptop charger) being misclassified as each other. Table I shows that these devices have similar reactive powers, which explains the misclassification.

From Table IV, it can be seen that using both real and reactive power, the classification accuracy increases to 100%. Although some of the electrical devices had similar real powers or similar reactive powers, devices were dissimilar when real and reactive powers were considered simultaneously, enabling the increased classification accuracy.

Results are encouraging for the condition when a single electrical device is in operation. Fig. 2 shows an example of a real power waveform when multiple electrical devices are operated simultaneously. Device recognition is more complicated in such a scenario. The real power waveform exhibits step changes that correspond to events (i.e., electrical devices turning "on" or "off"). While device recognition is more complex when multiple devices are operated simultaneously, the method of classification may not differ much from device recognition when they are operated separately. In this work, real power and reactive power were computed with respect to the “off” state. For multiple devices, events can be detected as change in the steady-state values. Electrical devices can be identified examining the difference in real power and reactive power, before and after an event. This methodology is applicable

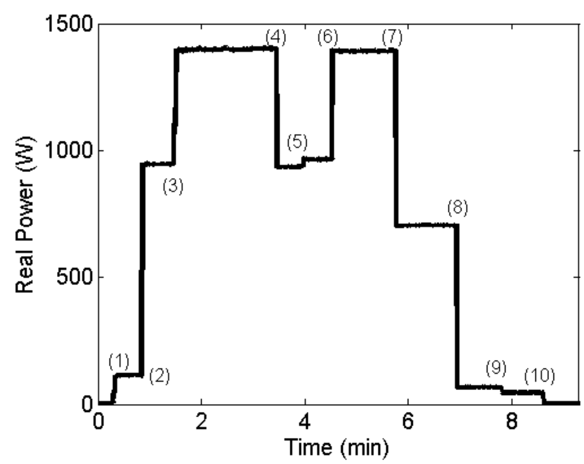

Fig. 2. Example of a composite real power waveform for multiple electrical devices. Numbers indicate events (i.e., devices turning "on" or "off"): (1) Laptop charger: On, (2) Electric kettle: On, (3) Microwave: On, (4) Microwave: Off, (5) Computer LCD Monitor: On, (6) Coffee maker: On, (7) Electric kettle: Off, (8) Microwave: Off, (9) Laptop charger: Off, (10) Computer LCD Monitor: Off.

when the load signature feature meets the feature-additive criterion, which the real power and reactive power do [6].

This work has only examined the steady-state load signature. Fig. 3 shows the current waveform for three different electrical devices as they transition from the “off” to “on” state; one can see that each device has a unique transient load signature that can be used to discern devices. Devices with similar real power and reactive power may still be distinguished based on their transient load signatures. Combining transient and steady-state load signatures serves as a means to improve device recognition accuracy. In addition, one can observe that the current waveform for the fluorescent lamp is not sinusoidal (Fig. 3c); additional steady-state features, such as harmonic content, can be used to further supplement the load signature.

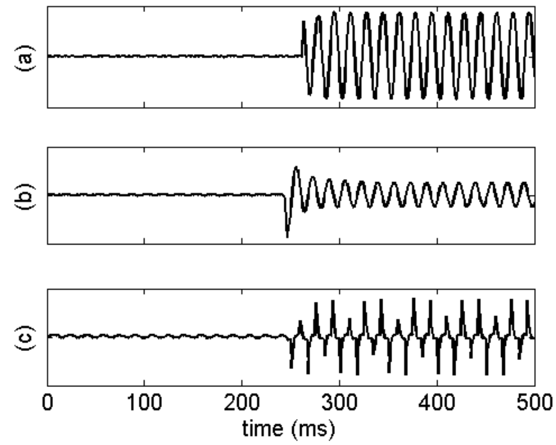

Fig. 3. Transient data for electrical appliances switching from "off" to "on": (a) Electric kettle, (b) Incandescent lamp, and (c) Fluorescent lamp.

V. CONCLUSIONS

A NILM system has been successfully demonstrated for the recognition of electrical devices when operated separately. Real power and reactive power are useful features to identify electrical devices and can serve as effective complementary features to one another.

In future work, we will experiment with the features proposed in this paper, along with the addition of other steady-state and transient features in order to determine robustly the operating state of certain classes of devices, such as low power loads, multi-state devices, continuously varying power devices, and devices with different power cycles. Research is also being extended to examine multiple devices in operation simultaneously, along with methods to disaggregate the individual loads from the composite signal. In addition, the work presented here employed a simple classifier (discriminant analysis). Advanced classifiers can likely achieve high classification accuracies even for a larger group of electrical devices and during simultaneous operation of multiple devices, and will be more suited for transient analysis (e.g., time delay artificial neural network and hidden Markov models).

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