Usage Monitoring of Electrical Devices in a Smart Home

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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 work proposes a feature-based model, using the real power and reactive power as features for describing the load signatures of individual devices.

METHODS

Experimental Setup: A NILM system (Fig. 1) was constructed to monitor various electrical devices connected to a common power bar. Current and voltage waveforms were measured at the input of the power bar. Current and voltage measurements were digitized using a 12-bit analog-to-digital converter at a sampling rate of 1 kHz (USB-6008). Data were stored on a computer and processed offline using MATLAB.

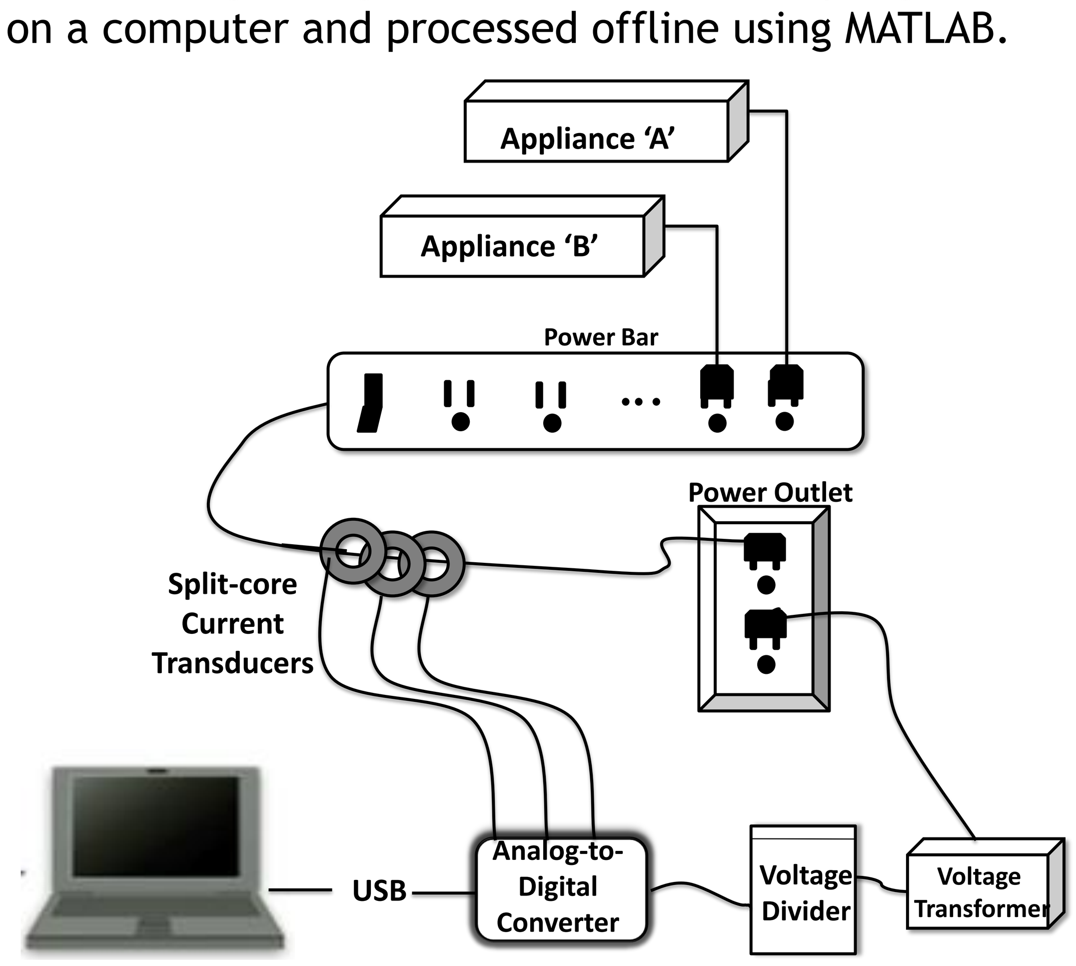

Figure 1. Experimental setup for the NILM system.

Data Acquisition: Five household electrical devices were used as loads in this study: electric kettle (Load 1), coffee maker (Load 2), computer LCD monitor (Load 3), incandescent lamp (Load 4), and fluorescent lamp (Load 5). We focus on disaggregation of two devices operating simultaneously. We have ten different combinations of two devices (5 devices choose 2 = 10). For each combination, a measurement trial was performed, operating each device separately and both devices simultaneously. Measurement trials are approximately 24 seconds in length, consisting of thre 8-second segments. Fig. 2 illustrates an example of one measurement trial for device 'A' and device 'B'.

Feature Extraction: Each 24-second measurement trial was broken down into non-overlapping 100 ms analysis windows. For load signature analysis, we only consider features that meet the feature-additive criterion [2].

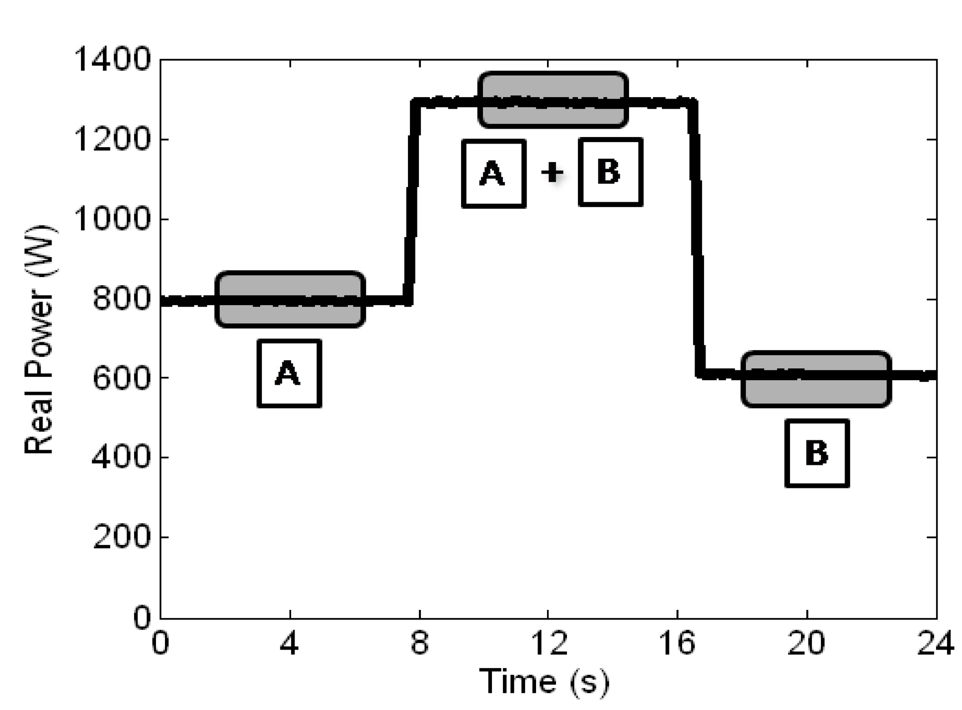

Figure 2. Real power versus time from an example measurement involving two electrical devices: device 'A' and device 'B'.

The real power meets the feature-additive criterion, and is used in this work for load disaggregation purposes. Instantaneous power is the product of instantaneous current and voltage waveforms, and the real power is the mean instantaneous power.

Training Set and Testing Set: Training data were selected from the measurement trials, when only one device was in operation. Fifty analysis windows from the middle of first segment and third segment of each measurement trial were used for training data (shaded area of the first segment and third segment in Fig. 2). For each device, there were 400 analysis windows in the training set.Testing data were selected from the measurement trials, when two devices were in operation (composite load signature). Fifty analysis windows from the middle of second segment of each measurement trial were used for testing data (shaded area of the second segment in Fig. 2). Testing data for device 'A' were computed by subtracting the mean feature value of device 'B' taken from the third segment of the measurement trial.

Pattern Classification: Classification was simply performed using Mahalanobis discriminant analysis [4].

RESULTS

Table I lists the mean real power (± one standard deviation) for the electrical devices, when operated individually and when operated in pairs. Diagonal elements in Table I contain the mean real power for the five individual electrical devices. For example, entry (1,1) of Table I is the mean real power for load 1 (computer LCD monitor). Entry (2,2) of Table I is the mean real power for load 2 (electric kettle). The off-diagonal elements contain the mean real power for the various combinations of two devices. The rows indicate the first device that is on and the columns indicate the second device that is on. For example, entry (1,2) of Table I is the mean real power when load 1 and load 2 are on simultaneously. As real power meets the feature-additive criterion, the summation of entries (1,1) and (2,2) (28.51 W + 798.49 W = 827W) should equal entry (1,2) (822.74 W).

Table I. lists the mean real power (± one standard deviation) for the electrical devices, operated individually and simultaneously.

Loads	Load 1	Load 2	Load 3	Load 4	Load 5
Load 1	28.51 ± 0.75	822.74 ±1.97	41.13±0.94	638.38 ±1.83	87.32±0.69
Load 2		798.49 ±9.97	859.75 ± 15.6	659.81 ±1.43	71.11±0.38
Load 3			608.42 ±2.50	623.56 ±2.95	1288 ± 2.52
Load 4				59.48±0.76	804.25±5.01
Load 5					13.31±0.63

Table II shows the classification confusion matrix. High classification accuracy (95%) 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 3 (coffee maker) is the only electrical device that is misclassified. Load 3 is misclassified as load 2 (electric kettle) 25% of the time. Load 2 and load 3 have comparable real power values (798.49 W and 608.42 W, respectively), which are much higher than the other devices; as well these devices the highest standard deviation values (Table I).

TABLE II. CLASSIFICATION CONFUSION MATRIX FOR REAL POWER. MEAN CLASSIFICATION ACCURACY 95%.

		Actual Load				
		Load 1	Load 2	Load 3	Load 4	Load 5
Predicted Load	Load 1	400	0	0	0	0
	Load 2	0	400	0	0	0
	Load 3	0	100	300	0	0
	Load 4	0	0	0	400	0
	Load 5	0	0	0	0	400

CONCLUSIONS

- A NILM system has been successfully developed and applied to an actual system involving five different electrical devices for the recognition of devices when operating simultaneously.
- The proposed method worked with high device recognition accuracy, demonstrating that real power is a useful feature to identify electrical devices.
- This work showed that we can separate out two different devices. The method can be generalized to more than two devices. Suppose *n* devices are operating simultaneously, and another device is turned on. The difference in the real power between the *n+1* devices and the *n* devices, should correspond to the load signature of the device that was turned on last.
- In future work, we will experiment with the features proposed in this paper, along with the addition of other steady-state and transient features (Fig.3) 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.

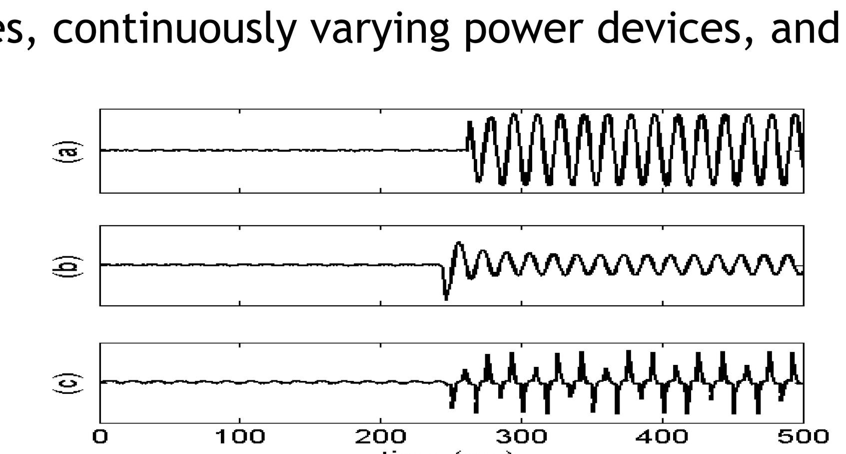

Figure 3. Transient data for electrical appliances switching from "off" to "on": (a) Electric kettle, (b) Incandescent lamp, and (c) Fluorescent lamp.

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