Classifying Energy-Related Events Using Electromagnetic Field Signatures

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Abstract. We propose a system that uses a set of mobile sensors, which fit on a keychain or ID/ access badge, for real-time feedback on a user's energy consumption. The work presented here is the first phase of the project where we demonstrate the feasibility of recognizing electrical activity in an uninstrumented space (e.g., home or office) with a simple sensor. We present a sensor which can eventually be made small enough to be able to install on a keychain or ID badge to be carried around during daily activities. The current phase of the project focuses on comparing the electromagnetic fields of several common appliances to determine unique signatures. In the next phase of this project, using our mobile sensors we can attribute energy-related events to an individual occupant over multiple locations and time.

Keywords: Energy consumption, EMF signatures, Decision Trees.

1 Introduction

Increasing demand of energy across the world has raised concerns about environmental impacts and limited availability of fuel. The United States Energy Information Administration (EIA) predicts world energy consumption will grow by 53 percent between 2008 and 2035 [1]. There is an immediate need to address the problem of depleting fuel and increasing pollution associated with electricity generation; energy consumption feedback is one of the remedies to address this problem. Research has shown that if consumers receive accurate and timely feedback about their energy usage, they can reduce their energy consumption by 20% [2-4].

The energy-related behaviors of every individual occupant in a building determine the aggregate energy consumption of a building. We believe that energy conservation can be achieved if we provide occupant-specific energy usage feedback. To provide individualized energy usage feedback it is necessary to gather more information about how each occupant is using energy. However, there is a dearth of gathered information in this research area [5], and what methods are useful for gathering this necessary information still remains an unresolved research question. A variety of products are available in the market that provide instantaneous feedback about energy usage but do not provide individualized energy usage [6]. Previous work in the area of

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electrical activity detection includes when Patel et al. [7] designed a system, tested in six different homes, which is plugged into an ordinary wall outlet to detect the transient noise generated by appliances and used that information to determine energy-related events. Although this approach is accurate, it cannot be used when calculating individual energy usage since it cannot identify which occupant initialized the energy-related event. Patel et al.'s system and our proposed system have similar aims, but our methods have distinct differences with distinguishable advantages in terms of mobility and ability to determine individualized energy usage. We believe influencing energy consumption must be addressed at the individual level to gain a significant and lasting impact. Therefore, a system that can attribute energy related events to an individual occupant over multiple locations and time may better address energy consumption concerns.

We propose a wireless system, which fits on a keychain or ID/ access badge. This compact wireless system moves with the user and can sense changes in illumination and power spikes indicating the user has turned an electrical equipment on and off, and that the user requires additional resources for heating, cooling, and ventilation. The system shares data with mobile phone sensors and intelligent sensors installed in the building for a detailed picture of individual energy use. The proposed system will alleviate the measurement problem by automating assessment and boosting efficiency by providing real-time feedback to users.

The work presented here is the first phase of the project where we demonstrate the feasibility of recognizing electrical activity in an un-instrumented living space with a simple sensor. The sensor perceives the entire spectrum of electromagnetic field (EMF). Electrical current developed in the antenna due to EMF is converted to a voltage. These data are fed into an algorithm to classify energy-related events.

2 Background

EMFs are invisible lines of force, which is the combination of an electric field and a magnetic field and exists wherever electricity is produced or used. Power supplied to home appliances generates extremely low frequency EMFs (e.g., 60 Hz in the U.S.). The motor, transformers, or any other electrical component of appliances generate EMFs with a variety of frequencies. For example, a hair dryer's heating coil radiates EMF at the frequency of 60 Hz, while the motor of the blower radiates EMF which is in the kHz range. The transformers in a computer may radiate EMF in kHz range, while the processor chip might emit EMF in the range of GHz. Each appliance has unique characteristics of EMF radiation, i.e., unique amplitude and frequency of radiation, which our algorithm uses for identification.

3 Experimental Setup

We collected scans of data using an EMF sensor (Figure 1), specifically the time series of EMF magnitude for individual appliances. A feature vector is generated by converting time series data to frequency domain and extracting features from it.

Five electronic devices (i.e., appliances and lighting) were scanned for their EMF signatures. Compact fluorescent lamps (CFL), incandescent bulb, fluorescent lamp, hair dryer, and small refrigerator were selected based on their common use as part of daily activities. Large appliances, such as a dishwasher or clothes dryer, will be examined in later studies but were not included in this initial pilot study of EMF signatures.

A photo capturing a typical data collection scene is shown in Figure 2. All readings were taken from approximately one foot away from the device. National Instrument's USB 6361 data acquisition system with sampling speed of 2 Mega samples per second was used for acquiring and saving data on a PC for later analysis. From the EMF data collected, FFT plots have been generated for each appliance examined.

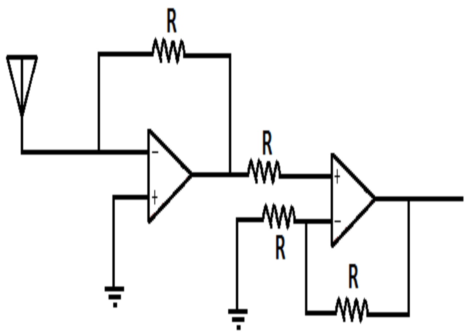

Fig. 1. Schematic of EMF sensor

Fig. 2. Experimental setup for data collection

4 Results

The plots in Figures 3-7 show the Fast Fourier Transform (FFT) of a one-second scan of each device, representing 2Msamples of data. We reduced this high-dimensional space to lower-dimensional space by building a histogram from the FFT plot for each device. Each bin of the histograms represents the mean of summed amplitudes of EMF for a range of frequencies. Frequency range of 0-1 MHz was divided into four sections. Each section was again divided into uniform subsections with widths of each subsection depending upon the importance of amplitude in particular frequency ranges. For example, 0-2kHz frequency range was divided into 100 sections of 20Hz each to create the first 100 bins of a histogram. The frequency range of 2-10kHz was divided into sections of 400Hz each. Further, frequency range of 10-100kHz was divided into sections of 10kHz each, and the range 100kHz-1MHz was divided into sections of 25kHz each. This procedure generated an array of 160 numbers, where each number represents mean of amplitude of EMF for a certain range of frequency. Figure 8 shows the histogram from the fluorescent lamp's EMF scan.

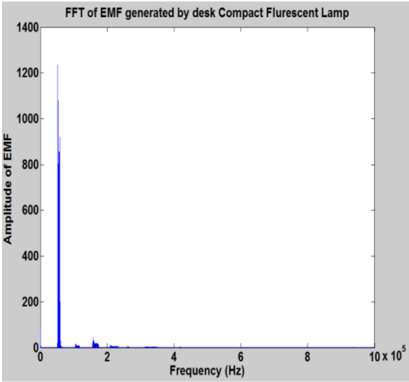

Fig. 3. FFT of compact fluorescent lamp

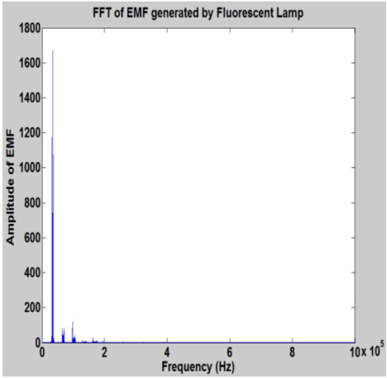

Fig. 4. FFT of fluorescent lamp

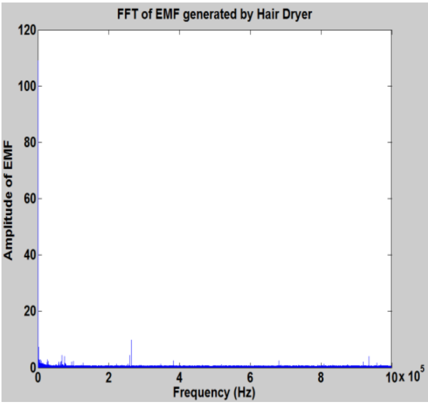

Fig. 5. FFT of hair dryer

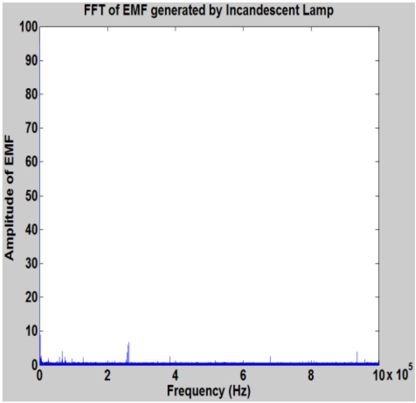

Fig. 6. FFT of incandescent lamp

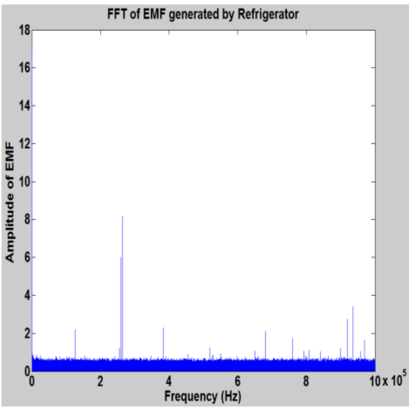

Fig. 7. FFT of refrigerator

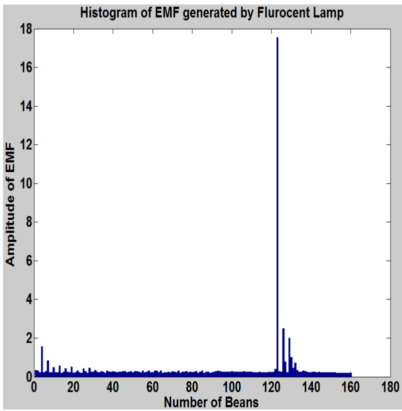

Fig. 8. Histogram of FFT for fluorescent lamp

The resultant histograms of each appliance were examined to empirically determine features that could classify each device, focusing on features that would provide a maximum value unique for each appliance as well as determining any thresholds that could be varied to discern different appliances. For example, the CFL used for this study emits significant EMF with frequencies in the range of 50-60kHz and 100-110kHz. Therefore, if bins number 125 and 130 are summed as one of the features, that feature separates the data well for an algorithm to identify the CFL; because bin 125 represents mean of amplitude of frequencies in the range of 50-60kHz and bin 130 represents mean of frequencies in the range of 100-125kHz, which produced high amplitudes of EMF when scanning the CFL. Similarly, signatures of each device were identified, and a feature was created from it. The features are listed in Table 1. The classification process manifests its substantial usefulness in that the features can be extracted from an unknown scan of EMF data and used to identify the type of appliance, which can be linked to its energy consumption. The raw data from an unknown scan can be processed for its FFT, from which a histogram is calculated and the features extracted. Furthermore, the features of an unknown scan can be sent as input into a Decision Trees (DT) algorithm to return the type of device. Therefore, an algorithm can provide feedback about what appliances are being used in a space based on EMF data mapped to EMF signatures of known devices.

Table 1. Listed are the features extracted from the histogram plots calculated from the data in this initial work

Feature no.	Feature
1	Sum of bins 125 and 130
2	Sum of bins 123 and 126
3	Mean of bins 10, 21, and 22
4	Sum of bins 25 and 28
5	Variance of bins 21 to 160

A comparison of EMF scans of the same appliance but taken at different times showed no marked difference. This consistency was as expected; since, for example, a device that emits a sizable amplitude of EMF at 90Hz and miniscule EMF at 110Hz is not expected to emit a sudden change in EMF data (e.g., give off a large 110Hz response and small 90Hz response at a later time) unless the electrical components of the device changed. Insomuch as the scans were sufficiently consistent, one scan from each appliance was used to build the DT structure for classifying the different appliances based on EMF data. The DT model (illustrated in Figure 9) was able to classify all five of the appliances studied in this pilot work based on example data from the features shown in Table 1. For example, feature 1 is very indicative of the CFL; if feature 1 is the largest value in an unknown EMF scan, the DT will return that the device being scanned is a CFL. This outcome makes sense in that feature 1 is made of bin 125 and bin 130 from the histograms. Bin 125's span includes 50-60kHz, and bin 130 includes 100-125kHz – both of which produced high amplitudes based on FFT's of the CFL's EMF scan. The remaining features differentiate the appliances such that the DT model can correctly return as output the type of device if given an unknown scan of one of the studied appliances as input. This initial work is in the proof-of-concept phase. Additional work is planned to (1) examine a large set of appliances, (2) test different techniques, such as exhaustive searches or correlation calculations, for identifying discerning features that differentiate the data and return high accuracy rates for classification, and (3) scan environments with multiple EMFs to classify multiple appliances simultaneously.

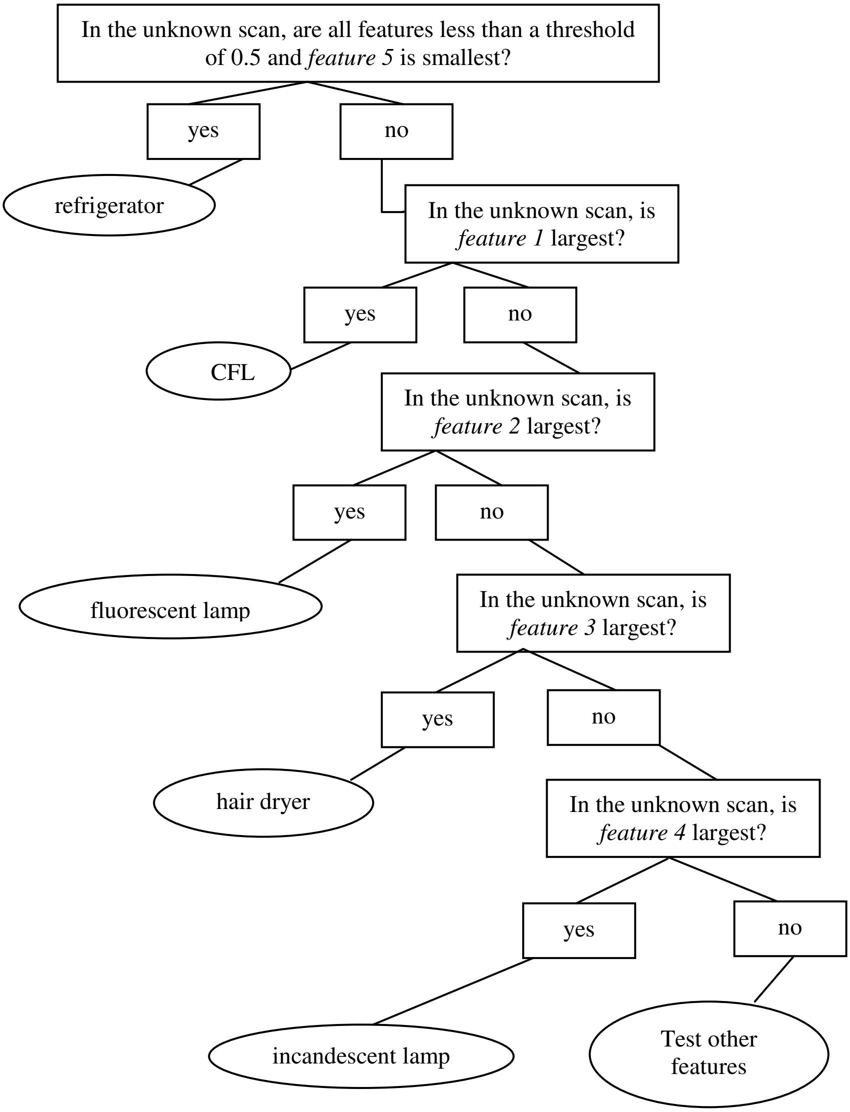

Fig. 9. Decision Tree model for this initial work

5 Discussion

This proof-of-concept phase of the research is promising; however, there are a few limitations to our current approach. The set of appliances used for this study was small and empirical selection of features might become complicated with increase in number of devices and when a combination of appliances working simultaneously is considered. In this study we maintained equal distance between every appliance and the sensor, which might not be true in practical use. We plan to work on optimizing the feature extraction process using a robust statistical method. Also, we plan to compare multiple machine learning algorithms like Neural Networks and Support Vector Machines against our current Decision Trees approach, to recognize the complex patterns of EMF signatures and infer on/off events of each appliance along with combinations of multiple on/off events.

Our future work is two-fold. First, we will design additional sensors to assist EMF signatures detected by the device described here, to make inferences about energy usage of individual users in a shared environment. Second, we plan to conduct user studies on perceptions of effective energy visualization. Feedback from these studies will inform us on how to provide users with useful information regarding their energy consumption. The visualization schemes will be incorporated into smart phone apps as feedback to users, to promote conservation on a real-time basis. Such a system must be able to detect when and how much energy is being used so that energy consumption can be monitored over time, given as information to a user, and used to calculate any change in consumption, preferably a reduction.

References

1. International Energy Outlook. U.S. Energy Information Administration (2011)
2. Darby, S.: The effectiveness of feedback on energy consumption: A review for DEFRA of the literature on metering, billing and direct displays. Environmental Change Institute (2006)
3. Seligman, C., Darley, J.M.: Feedback as a means of decreasing residential energy consumption. Journal of Applied Psychology 62(4), 363–368 (1977)
4. Rosenwald, M.S.: For Hybrid Drivers, Every Trip is a Race for Fuel Efficiency. Washington Post (2008)
5. Kavgic, M., Mavrogianni, A., Mumovic, D., Summerfield, A., Stevanovic, Z., Djurovic-Petrovic, M.: A review of bottom-up building stock models for energy consumption in the residential sector. Building and Environment 45, 1683–1697 (2010)
6. Kulkarni, A.S., Welch, K.C., Harnett, C.K.: A review of electricity monitoring and feedback systems. In: Proceedings of IEEE Southeast Conference, pp. 321–326 (2011), doi:978-1-61284-738-2/11
7. Patel, S.N., Robertson, T., Kientz, J.A., Reynolds, M.S., Abowd, G.D.: At the flick of a switch: Detecting and classifying unique electrical events on the residential power line (Nominated for the best paper award). In: Krumm, J., Abowd, G.D., Seneviratne, A., Strang, T. (eds.) UbiComp 2007. LNCS, vol. 4717, pp. 271–288. Springer, Heidelberg (2007)