A study on the feasibility of automated data labeling and training using an EMF sensor in NILM platforms

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Abstract. Non-Intrusive Load Monitoring (NILM) has been studied for a few decades now as a method of disaggregating information about appliance level power consumption in a building from measurements obtained at a centralized location in the electrical system. The training phase required at the beginning of a NILM setup is a big hindrance to wide adoption of the technique. One of the recent advances in this research area includes the addition of an Electro-Magnetic Field (EMF) sensor that measures the electric and magnetic field around an appliance to detect its state. This information, when coupled with the aggregate power data, can effectively train a NILM system almost automatically, which is a significant step towards automating the training phase. This paper explores the theory behind the operation of the EMF sensor and analyzes the feasibility in terms of automating the training and classification process. It then outlines our plan for further analysis.

1. Introduction

Electricity constitutes 41% of total annual energy consumption in the United States (US), 67% of which is produced from fossil fuels (Annual Energy Review 2009). Hence, the impending shortage of non-renewable resources does not bode well, both for the US and the world (Fuel Statistics 2012). Until electricity production through renewable sources becomes advanced enough to sustain all demand, the only way forward is to reduce consumption. McMakin et al. notice that the most significant energy savings can be realized by changing people's habits (McMakin, Malone & Lundgren 2003). Darby claims that immediate feedback about consumption patterns can reduce consumption to produce savings of up to 15% (Darby 2006) to 20% (WBSCD tech report, 2008). Considerable research has been underway in efforts to provide meaningful feedback about electricity consumption to consumers.

1.1 Background

One form of meaningful feedback about electricity consumption could be the appliance level breakdown of electrical energy usage in a building. Connecting appliances directly to energy meters is one way of doing this but hardware, operation and installation costs prove to be major drawbacks in this case (Rowe 2006). A less invasive approach would be one pioneered in the 1980s: Non-Intrusive Load Monitoring (NILM) (Hart 1992). NILM typically involves an energy meter at the circuit panel level that can be used to monitor changes in voltage and/or current that are produced when appliances being fed through that circuit change states. Based on features of the signal changes (like change in magnitude, harmonics), the system identifies which appliances are turned ON at any given moment, and their respective power consumption levels.

Although an intriguing concept in theory, the problem of identification and disaggregation becomes incredibly complex as the number of appliances in the house increases. As of date, no complete NILM solution suitable for all types of household appliances has been discovered (Zeifmann & Roth 2011). Roth and Zeifmann note that the available solutions are either unsuitable for some appliances or still at an early developmental stage and that no complete set of robust and widely accepted appliance features has been identified (Zeifmann & Roth 2011)

1.2 Sensor-aided NILM

Numerous attempts have been made to either aid NILM or act as substitutes (Zeifmann & Roth 2011). Some researchers, for example, have used a combination of several radio-enabled sensors (magnetic, acoustic, and light) that send information to a central "fusion-center" that calibrates the sensors automatically and estimates power consumption (Kim, et al., 2009). Other authors cite the difficulty of using magnetic sensors presented by Kim et al. as the reason for using an Electro Magnetic Field (EMF) event detector, which works with "a more amplified signal" (Rowe, Berges & Rajkumar 2010). The sensor system presented by Rowe et al. processes the measurements of the electro-magnetic field locally to detect changes in the operating state of an appliance. This information is then synchronized with main-circuit level data (performing NILM) to measure the appliance power consumption. Some researchers have also tried using multi-mode sensor fusion schemes to perform automated annotation with some success (Schoofs, et al., 2010). A system that fuses NILM with an indirect sensing platform and performs automated calibration, training and annotation seems to be an ideal solution. With that motivation, we explore further the possibility of using an EMF event detector with the same wireless sensor-networking platform used in by Rowe et al. to automatically train a NILM system (Rowe, Berges & Rajkumar 2010).

1.3 Current state of affairs of EMF detectors

Rowe et al. note the following observations from their experiments with an EMF sensor they developed based on the FireFly wireless sensor networking platform (Rowe, Mangharam & Rajkumar 2006):

· The strength of detected magnetic field (H) varies directly with coil size of the EMF detector.
· H varies inversely with the distance from the appliance.
· The antenna length in the JFET receiver is proportionally related to the electric field output at the EMF sensor.
· Possible cross-talk[1] and the difficulties of detecting state transitions in appliances with multiple operating states, are cited as limitations.

1.4 Further Explorations

This paper will explore the physical principles behind the EMF detector with the goal of motivating algorithm development for appliance classification. It will explore how distance and orientation of the sensor affects the quality of the magnetic field signal, and propose suitable features to be selected for event detection and classification. Some results of projection of the individual appliance signatures into different vector spaces obtained by applying principal components and linear discriminants analyses will also be shown. Finally, the limitations of this approach and the challenges that need to be addressed in future work will be discussed.

2. Theory

The EMF sensor operates under the principles of electromagnetic induction. Any conductor with current flowing through it will generate a magnetic field around itself. This field can be estimated for infinitely long wires using the Biot Savart's Law:

$$B= \frac{\mu I_O}{2 \pi r} sin\ (\omega_0 t) \tag{i}$$

Here r is the distance of the wire from the point of reference and $I_O sin\ (\omega_0 t)$ is the current flowing through the wire, modeled as a harmonic oscillation with amplitude I_O and frequency ω_0. The direction of this field will be along the cross product of r and the direction of current flow. (Jackson 1998).

For better illustration of the theory, it will be assumed that the sensor sits next to the wire that connects an appliance to the voltage source. The magnetic field is constantly changing in amplitude as $\omega_0 t$ changes. This change in magnetic field causes a change in magnetic flux ($\phi = \int B\ dA$) through the coil. Here A is the area of the coil. This variability in the magnetic flux induces an electromagnetic field E which, from Faraday's Laws, can be calculated as

$$E = \frac{d\phi}{dt} \tag{ii}$$

Putting in the values for ϕ and B, we get:

$$E= K(r)\ cos\ (\omega_0 t) \tag{iii}$$

Here K(r) is a function that depends on the distance of the solenoid from the current carrying wire, and is constant for any fixed distance and solenoid (Jackson 1998).

This implies that the EMF induced in the coil is 90 degrees out of phase with the current in the wire, and that measurements with the EMF detector should show this. Figure 1 shows data collected with this sensor, along with measurements of the current in the wire.

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[1] Cross-talk, here, refers to the electromagnetic field interference from nearby appliances or other sources.

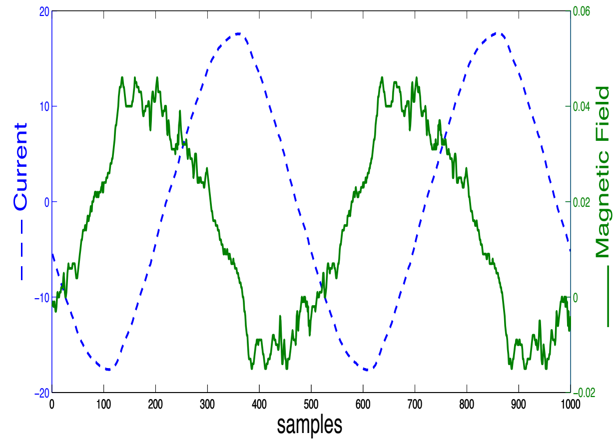

Figure 1. Current (dotted) versus Magnetic Field (solid) for a heater. The two are 90 degrees out of phase, as expected.

As can be seen from equation (i), a change in the distance r of the solenoid from the current source would only affect the amplitude of the sinusoidal magnetic field at the solenoid, and not the sinusoidal nature of the signal.

Similarly, any change in orientation of the solenoid results in further scaling of the signal without changing the periodicity and shape of the magnetic field signal. To further understand this, one can visualize the angle that the axis of the solenoid makes with the direction of the magnetic field- say θ. Any change in θ would result in the magnetic field at the new solenoid position being a projection of B, i.e. B cos θ.

Hence, a normalized signal remains unchanged in shape regardless of the orientation of the sensor and its distance from the current source. Figure 2 serves to elucidate this point.

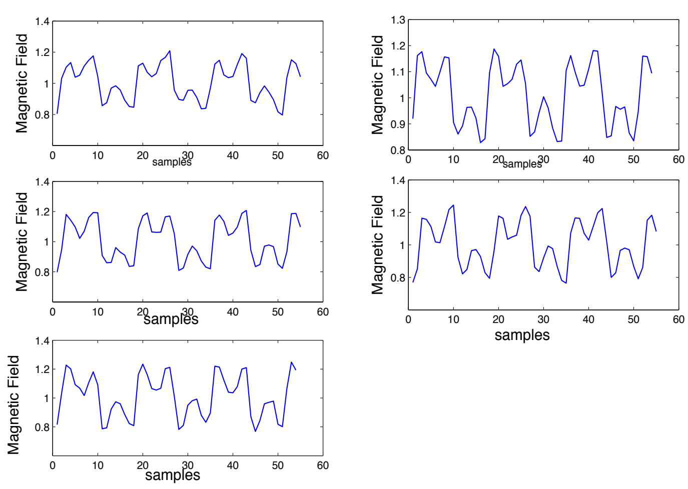

Figure 2. Magnetic field measurements of a heater with distances of: 10 cm (top left), 11 cm (top right), 14 cm (middle left), 17cm, (middle right) 20 cm (bottom left)

These observations indicate that a single period of the steady-state magnetic field measurements obtained when the appliance is in operation would contain enough information to characterize the signals.

Before starting the automated classification of individual appliances, it is helpful to estimate the level of classification that can be expected with the EMF detector. Since only the magnetic field is being measured, there is no way to obtain phase information (i.e. the phase difference between the voltage and the current). Typically, a NILM setup will utilize the phase values to calculate Real and Reactive power consumption of an appliance to further classify them (Hart 1992). Since the signal will not have that information, classification of load types into categories such as inductive, capacitive, resistive etc. will not be expected. Perhaps, the only classification of loads that can be predicted with certainty is that of linear versus non-linear loads.

3. Preliminary Results

Data was collected for ten household appliances using the same EMF detector presented in (Rowe, Berges and Rajkumar 2010) and a National Instruments (NI -9215) data acquisition card. To ensure that most of the relevant information in the signal was captured, a sampling rate of 30KHz was chosen. A single period was then taken from the steady state of operation for each of the appliances which resulted in a vector of 500 samples for each signal of each appliance. The appliances that were used were: air-conditioner, compact fluorescent light bulb, incandescent light bulbs (100W and 60W) , refrigerators (two), microwave oven, vacuum cleaner, fan and space heater. Before classification is performed, the isolated periods were projected onto a different vector space with the goal of reducing redundancy by keeping only the features that are useful for classification purposes.

As one form of projection, Principle Component Analysis (PCA) was performed on the data set. The goal behind PCA is to keep only the features that highlight the variance among the dataset, and get rid of any correlation that might exist (Marsland 2009). This results in a reduction in redundancy and dimensionality. Figure 3 shows how the individual appliances clustered after projecting the original data into the space spanned by the first two principal components. In this case, the first two components capture 84% of the total variance in the data. The data for the same appliance (and appliance state) cluster fairly well. To assess if this is a good projection for classifying our data, a simple K-means clustering was done on the projected signal (Marsland 2009). K-Means clustering on the projection of the data onto the first three principle components give an accuracy of 90.6%.

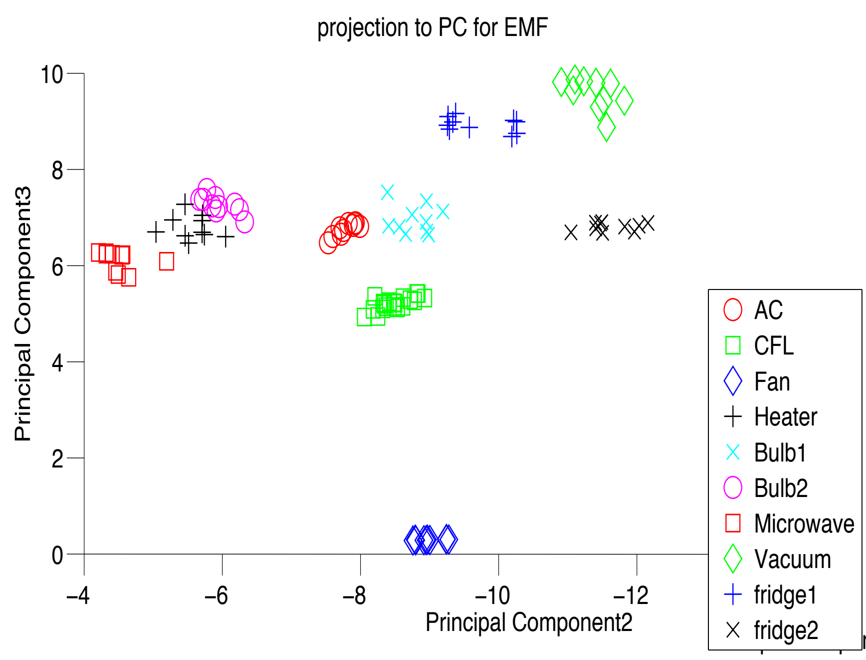

Figure 3. Projection of appliance signatures onto second and third Principal Components.

After this, Linear Discriminant Analysis (LDA) was performed on the dataset. This analysis projects the data on axes that maximize interclass variability while preserving intra-class features (Marsland 2009). The results are shown in Figure 4. The data clustered fairly well and K-Means clustering on the projection of the data onto the first three linear discriminant axes gave an accuracy of 100%.

One common technique in image classification is to perform LDA on the data projected on Principle Components. With that as motivation, LDA was performed on the data processed through PCA. The results are shown in Figure 5. K-Means clustering on this data gave an accuracy of 87.7%.

After having found a good orthogonal basis for projection (LDA), the next step is to deploy classification algorithms on the data to automate the classification phase. We are looking to explore Neural Networks and Support Vector Machines for this purpose on our data after it has been projected into each of the above axes.

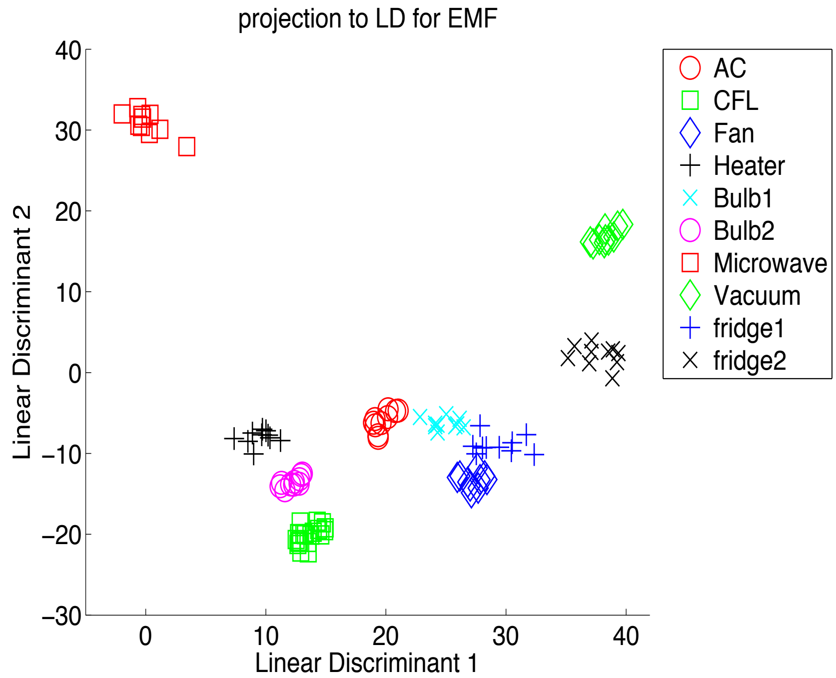

Figure 4. Projection of appliance signatures onto first two Linear Discriminant axes.

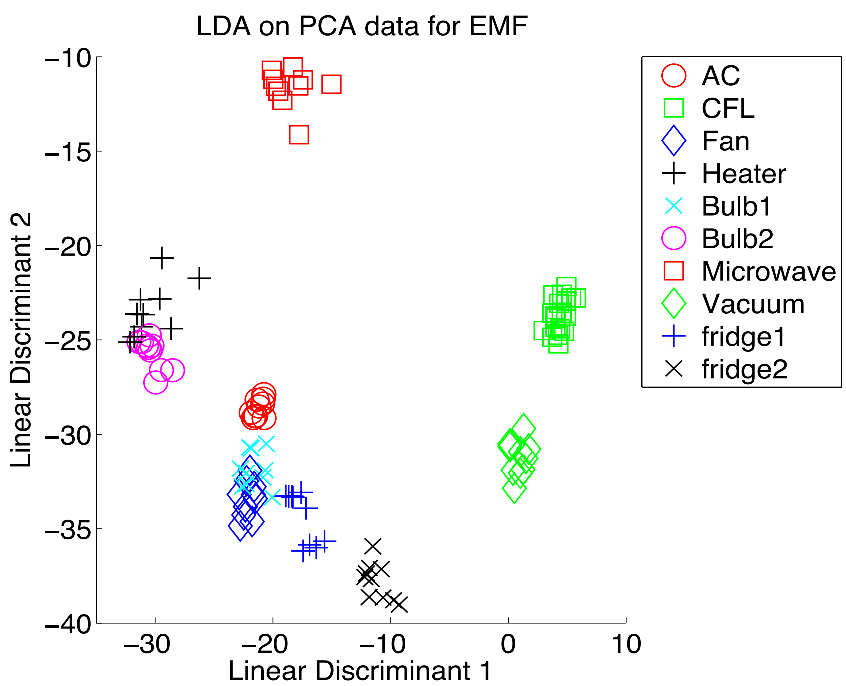

Figure 5. Projection of data projected onto PC's onto LD axes. The circles have been drawn manually to highlight clustering.

4. Limitations

The biggest challenge in using EMF sensors to perform event detection comes from noise sources from other nearby appliances. False positives are a big issue in this case and our analysis has only focused on isolated appliance signatures so far. Eventually, we plan to study projections of mixed signals and see how well individual events can be isolated.

This analysis has also only focused on steady state signatures, but there will be information about events on the transient states as well that we hope to exploit in our algorithms. The issue of finite state appliances, as noted by some authors, still remains a concern (Rowe, Berges & Rajkumar 2010), but since we are only interested in event detection, knowing the ON and OFF state signatures is enough for our purposes.

5. Conclusion

This paper outlined the motivation behind NILM and the need for sensor-aided information, especially in the training phase. It discussed the analysis that has already been performed on an EMF sensor developed using a FireFly wireless sensor networking platform, and the current limitations of the approach. It then presented a case for using a single period from magnetic field signal during steady-state operation of the appliance as an invariant feature that could be used for automatically classifying the appliances being monitored regardless of the orientation of the sensor or its distance from the appliance. Some preliminary results from performing PCA and LDA on the collected data, which show promising signs of clustering by appliance type were also presented. Finally, the limitations of this approach and plans for further research were discussed.

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