Detecting IT and Lighting loads using Common Mode Conducted EMI Signals

Manoj Gulati Shobha Sundar Ram Angshul Majumdar Amarjeet Singh
IIIT-Delhi (India)
(manojg, shobha, ansghul, amarjeet)@iiitd.ac.in

Abstract **- Office buildings are the major consumers of electricity after residential buildings. In order to achieve long-term energy sustainability, energy disaggregation techniques have to account for office buildings, especially for electronic appliances. Prior work proposed a new sensing technique using EMI signals to detect electronic appliances. However, it is known to have significant limitations. In this work we propose a new feature and a sensor for EMI sensing. We also evaluate the efficacy of both of these features on a real dataset and demonstrate an improvement in appliance detection accuracy up to 87.3% vs. 49.6% accuracy from previous feature.**

Keywords — Electromagnetic interference (EMI); Common mode (CM); Differential mode (DM).

I. Introduction

Office buildings account for the majority of the energy consumption (approx. 20%) after residential buildings and electronic appliances like IT loads and lighting are the second highest major consumers. However, most of the existing NILM methods, using low frequency smart meter data fail to detect these loads due to time-varying power consumption of these loads. Recently, a promising technique, using high frequency EMI signals to detect electronic loads is proposed [2]. Most consumer and power appliances with switched mode power supplies (SMPS) inject EMI into the power lines. EMI from appliances is coupled in differential mode (DM) or common mode (CM). Details of DM and CM EMI and their coupling mechanisms can be found in [1]. The authors in [2] postulated that appliances generate a unique and time-invariant DM EMI between the phase and neutral terminals, which can be exploited as a reliable feature vector for appliance classification. However, [3] has shown several of the challenges associated with using the DM EMI as a reliable feature vector. In this work we propose CM EMI as a feature for appliance detection, which is having following merits over DM EMI -

a). CM currents, which are generated at low frequencies due to capacitive coupling. Hence, are likely to attenuate more gradually with the increase in line impedance.

b). Earth wire (where the CM measurements can be made) is not meant for conduction of mains power supply and only meant for common mode leakage currents. As a result the noise floor on CM measurements is likely to be much lower than DM.

c). In contrast to DM EMI, most appliances are not fitted with CM filters since CM noise is far less likely to impact the functioning of neighboring appliances.

II. Measurement of CM and DM components

A single-phase power supply (or a single branch of a three phase power supply) consists of three power lines: the phase, neutral and earth, which are characterized by transmission line impedances Z. The power supply may be single ended or split phase with a 230V, 50Hz (Indian standard) between phase and neutral. In our work, we consider the more commonly found single ended supply where the neutral and earth terminals are shorted at the distribution transformer outlet. In the case of split phase power supplies, the CM and DM can be measured by the sum and difference of phase (V_p) and neutral (V_n) voltages with respect to the earth measured at the power supply.

$$V_{CM} = V_p + V_n \quad (1)$$

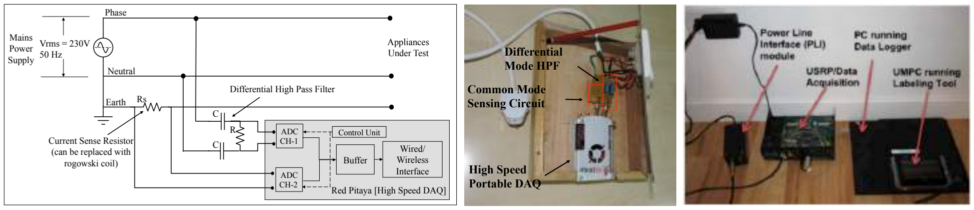
$$V_{DM} = V_p - V_n \quad (2)$$

In single-phase power supplies, DM can be measured by the potential difference between the phase and the neutral. But the measurement of CM is more challenging. One method is to measure V_{dm} and V_p independently and estimate V_{cm} by subtracting V_{dm} from V_p. The advantage of this technique is that it can be applied to both two pin and three pin appliances. However, in practice, the performance of this technique is poor due to (1) the phase mismatch between DM and CM components and (2) because the magnitude of DM measurements usually exceeds the magnitude of CM by a few orders due to power supply harmonics. A second method is to directly measure the earth currents, which correspond to the CM components. The main advantage of this method is that the background noise across the earth lines is much lower than the phase and neutral lines. However, this technique can only be applied to three pin appliances due to the absence of a physical earth line connection in two pin appliances.

III. Proposed Work

A. Plug and Play EMI Sensor Using Conducted EMI for Appliance Detection

We propose a low cost, portable sensor, made with off-the-shelf components, that is capable of simultaneously measuring both the CM and DM EMI components from appliances on the single phase (single ended) power lines. The DM component is estimated from the potential difference between the phase and neutral lines as shown in Figure. 1(a). The power signal (230V, 50Hz) and some of its lower harmonics are removed



(a) (b) (c)

Fig. 1: (a) Proposed EMI Sensor which is capable of simultaneously sensing CM and DM EMI on the mains power lines; (b) actual prototype; (c) Reference viewgraph of the DM EMI sensor developed previously by [14]. The power line interface in (c) corresponds to the high pass filter in (b) and the USRP in (c) corresponds to the DAQ in (b).

from the signal through a differential high pass filter (F_c= 9kHz). The CM signal is estimated by measuring the voltage across a current sense resistor (R_s) on the earth line. Note that while the current sense resistor offers a cheap technique for measuring the CM currents, the deployment introduces a break in the connection between the power supply and the appliance (or the power line feeding multiple appliances). A non-intrusive, but more expensive alternative, would be to introduce a current sensing coil around the earth line. The data acquisition is carried out with the open source high speed Red Pitaya board. Both the CM and DM data are acquired at a sampling frequency of 15.625MHz and stored in internal buffers. The data from the buffers can be loaded into a server or CPU for further processing. The equivalent circuit of our proposed sensor is shown in Figure. 1(a), Figure. 1(b) shows the actual prototype and Figure. 1(c) shows a contrasting sensing solution developed in [2].

B. Signal Processing and Feature Extraction

Consider that there are I appliance categories and J instances of each category. Accordingly, $x^s_{i,j}(t)$ represents a single trace or sample from S time-domain EMI traces measured for the j^{th} instance of appliance category *i*. The time-domain data gathered by the sensor for each appliance are not directly used as a feature vector for classification because the measurements are not synchronized. Instead, we hypothesize that the CM EMI data from each appliance has a unique histogram that can be used as its signature. The histogram, derived from each sample (s), is obtained by binning the time domain data based on its magnitude. The distribution can be uniquely described by certain statistics. In this work, we extracted the following features from the histograms for classification: {entropy, skewness, interquartile range, kurtosis, percentile-75, range, maximum, median, percentile-90, mean absolute deviation}. The features are listed in the order of their effectiveness towards classification and form a vector for each sample trace ($f^s_{i,j}$). Features such as minimum and percentile-25 are not used since they look identical across multiple classes when we consider the magnitude of the measured data.

The data from one instance (j'), of appliance category (i'), are used for training while the data from the remaining instances (test instances $j \neq j'$) are used for testing. The mean of the statistics, $\hat{f}_{i',j'}$ from all the traces corresponding to j' , is used as the training model. Each trace of the testing instances (j), corresponding to appliance category (i), is treated as a separate test case. A test case is classified based on the minimum Euclidean distance between the test vector, $f^s_{i,j}$, and the training models for all the appliances as shown below.

$$\min_{i'} \left\| f^s{}_{i,j} - \hat{f}_{i',j'} \right\|_2^2 \vee i, j \neq j' \qquad (5)$$

IV. Experimental Setup

The common IT loads and lighting sources in most offices are CPUs, LCD monitors, laptops, telephones, modems, wireless routers, printers and CFL lamps. Smart meters have not been successful in detecting these appliances. Additionally, these appliances are fitted with high quality EMI filters to reject DM EMI emission. Therefore, they are difficult to detect with DM EMI data. In this section, we show the utility of CM feature vector for successfully detecting some of these appliances. In most office setups, multiple appliances of the same type (make and model) are used due to logistical reasons. Due to practical considerations, only a single instance of an appliance can be used for generating training data for learning the features. However, once the features are learnt, they must be useful for detecting other instances of the same appliance type. Therefore, in this work, our classification algorithm is trained on data from a single instance of each appliance category and is used to detect other instances of the same type. This test protocol marks a significant departure from previous works in this domain. We carried out the measurements inside the office precincts of our institute where the appliances are powered from an uninterrupted mains power supply (UPS). The EMI sensor, described in the previous Section, is connected to an outlet on an extension cord that is connected to the UPS. Additional measurements are made on the power line without connecting any of the appliances. This is useful in determining the background noise on the power lines in the absence of the appliance under test (AUT). The EMI data collection from the twenty-five individual appliances (five instances of each of the five appliance categories) spanned over a week from which we considered a data set spanning 5-6 hours (which includes measurement and logging time). In the next two Sections, we discuss the measurement data and classification results for all appliances.

V. Measurement Results

Time-domain CM and DM EMI are measured simultaneously for each individual instance of an appliance at a sampling

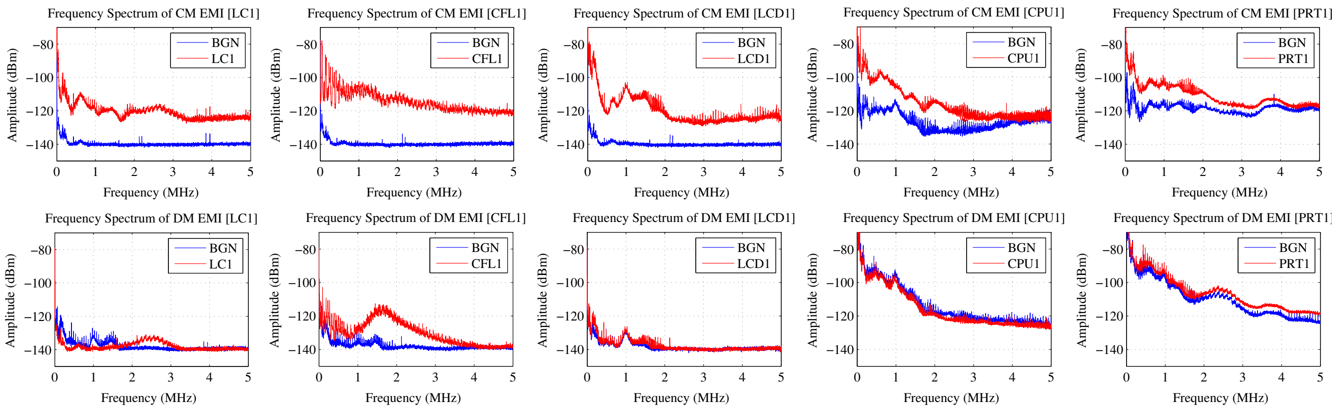


Fig. 2: Frequency domain plots showing (a) common mode EMI and (b) differential mode EMI measured from 5 appliances. They are Laptop charger (LC), CFL, LCD, CPU and Printer (PRT) (along with background noise (BGN) on the power lines before the appliance was turned on).

frequency of 15.625MHz. Each time domain trace is 150ms long. A total of 10 traces are collected for every appliance instance and there are 5 instances of each appliance. Corresponding amount of background data are also collected.

A. *Frequency Domain Results*

Figure. 2(a) and Figure. 2(b) show the frequency domain CM and DM signatures of an instance of each of the laptop charger (LC), CPU, CFL, LCD monitor and printer (PRT). The frequency range of interest is from DC to 5MHz. Before turning on the appliance, the background noise on the power lines are measured for each case. This exercise was carried out to monitor the change in the background noise characteristics in the power lines during the measurements. We note that across all the figures, the background noise in the CM measurements (−100dBm to −130dBm) is lower than the DM measurements (−60dBm to −120dBm). This is possibly because of the absence of power line harmonics and other fluctuations on the earth line where CM is measured. Secondly, we observe that above 4MHz, the frequency data look identical for all the appliances as it is dominated by the background noise on the power lines. Finally, the CM signatures are reasonably consistent across multiple instances of the same appliance make and model. This is not true for the case of DM. These results are not shown here due to constraints of space. In the case of the laptop charger (LC) and LCD monitor, a broad band CM noise can be discerned over the background noise floor, up to 2MHz. The average signal to noise ratio over this band of frequencies is 15dBm and 20dBm respectively. However, the poor DM to noise ratio, clearly shows that the EMI filters in the laptops and monitors have successfully removed all DM EMI. Therefore, the detection of these appliances is likely to be very poor if DM data are used as feature vectors for classification. Considerable CM and DM EMI are observed in the case of CFL. The average SNR across the entire frequency domain, are 30dB and 25dB respectively for CM and DM respectively. The EMI signatures from CFL are characterized by the fundamental peak, at 41.4kHz, corresponding to the switching frequency of the power supplies within the CFL and its higher order harmonics. Therefore, we anticipate that both CM and DM data can be successfully used for identifying CFLs. In the case of the CPU and printer, the background noise on the CM measurements were occasionally high. This may affect the classification results in these cases. In this work, we chose to not use the frequency domain data for machine learning and classification since a large portion of the data, from 4MHz to 7.8125MHz (half the sampling frequency) show significant overlap across the multiple appliances.

B. *Histograms*

Time domain measurements are not synchronized in any manner. Hence they show considerable variation across multiple instances of the same appliance and across time depending on the starting time (and phase) of the measurements. Therefore, these traces cannot be directly used as signatures for appliance classification. Figure.3 shows the normalized number of counts per bin (histogram) of the magnitude of the CM EMI from 1 (out of 5) instances of each appliance category along with background class. Each of these histograms are drawn from data from a single time-domain trace of 150ms. The figures show the following features: the histograms of the measured voltages show considerable variation across different appliance categories. The most distinct histogram belongs to the CFL and the background noise category. CPU, printer and LCD have roughly similar histograms. However, due to distinct peak values and width of slope in histograms, statistics such as kurtosis and skewness are able to capture this dissimilarity. Therefore, statistics (listed in Section III.B) that describe the histogram can form the basis for appliance detection and classification. DM data that are dominated by background noise show very similar histograms across multiple appliance categories. These histograms are not shown here due to constraints in space.

VI. Classification Results and Discussion

As mentioned earlier, there are 6 categories in the classification - *{LCD monitor, Laptop Charger (LC), CFL, CPU, Printer (PRT) and Background (BGN)}*. The last category, *{BGN}*, implies the absence of any of the other five IT appliances on the power line. 10 samples were measured for each of the 5 instances of every appliance category. Thus, I = 6, J = 5 and S = 10 based on the definitions provided in Section III.B. The training model is the vector formed from the mean of the statistics drawn from the histograms

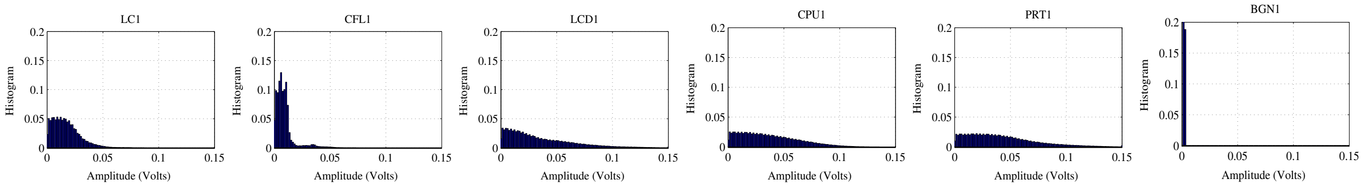


Fig. 3: Histogram (normalized number of counts per bin) of CM EMI data, of five appliances (from 1 of 5 instances) (a) Laptop charger (LC) (b) CFL (c) LCD (d) CPU (e) Printer (PRT) (f) Background noise (BGN) (when none of the appliances were operational).

corresponding to the samples of the training instance (20% of measured data). Each of the samples from the remaining four test instances form an individual test case (80% of measured data). Five-fold cross validation is carried out where the training and testing instances are swapped. As a result, there are a total of 200 (4 x 10 x 5) test samples corresponding to each appliance category. Each test case is assigned to one of the 6 appliance categories on the basis of the *minimum Euclidean distance* between the test feature vector and the training models as described in (5). We carry out the classification process using CM EMI data and then repeat the process with DM EMI data. We present the appliance confusion matrix along with precision and recall results from the nearest neighbor based classification algorithm on a per appliance basis in Table I(A) and Table I(B). The column headers, in the tables, indicate the classification classes whereas the row headers indicate the test classes. The highlighted features in the table indicate correctly identified test cases. Together, the precision and recall indicate the accuracy of the classification algorithm and the efficacy of the chosen feature vector.

The following inferences can be drawn from the results: the average CM EMI precision and recall results (87.3% and 86.8% respectively) are far superior to the DM EMI precision and recall results (49.6%, 45.2% respectively). This validates the key hypothesis of our paper that CM EMI is a far superior feature for IT appliance detection compared to DM EMI. The poor performance of the DM results can be attributed to the high background noise (−60 to −120dBm) that dominated the DM measurements as seen in Figure. 2(b). The *background* results in the CM EMI case is 100% (both precision and recall) compared to the low values for DM EMI. This is because of the distinct low noise floor that was observed in the CM EMI measurements due to the absence of the power signal and its higher order harmonics. Past research efforts, using either smart meters or DM EMI, have reported the challenges in detecting IT appliances such as laptop chargers, LCD monitors and printers. Since these appliances are usually fitted with powerful DM EMI filters, they show very poor performance with respect to DM EMI (16.5%, 33.5% and 39.5% recall for laptop chargers, LCD monitors and printers respectively). The high precision and low recall value for printers, in the DM EMI case, is due to the poor SNR in the measurements due to the high background noise values. The classification of printers is therefore, largely on the basis of background noise rather than EMI signal itself. Nevertheless, these appliances are accurately detected with their CM EMI signatures (above 90% precision and recall for laptop chargers and printers; 72% for LCD monitors). CFLs can be accurately detected using either DM EMI or CM EMI data due to their

TABLE I - RESULTS FROM NEAREST NEIGHBOR BASED CLASSIFICATION ON (A) CM EMI DATA AND (B) DM EMI DATA ON 6 CLASSES

	BGN	LC	LCD	CFL	CPU	PRT	Recall (%)
BGN	200	0	0	0	0	0	100
LC	0	197	3	0	0	0	98.5
LCD	0	15	144	0	33	8	72
CFL	0	0	0	200	0	0	100
CPU	0	0	12	0	119	69	59.5
PRT	0	0	1	0	17	182	91
Precision (%)	100	92.9	90	100	70.4	70.3	

	BGN	LC	LCD	CFL	CPU	PRT	Recall (%)
BGN	99	30	61	0	10	0	49.5
LC	106	33	43	0	18	0	16.5
LCD	87	29	67	0	17	0	33.5
CFL	3	4	0	193	0	0	96.5
CPU	51	22	38	0	69	20	34.5
PRT	7	5	12	0	97	79	39.5
Precision (%)	28.1	26.8	30.3	100	32.7	79.6	

strong and unique signatures and the absence of any type of EMI filters (DM and CM). Desktop CPUs show some improvement from DM EMI to CM EMI (from 35% to 60%). However, these appliances still remain challenging to detect. This can be attributed to the high background noise floor in the CM measurements of the CPUs (refer Figure. 2).

VII. CONCLUSION

In this work (and all other prior works related to EMI sensing), the feature extraction for classification is carried out when the appliances are individually connected to the power lines. We have limited the study to one appliance at a time in order to evaluate the signal quality, stability and consistency across multiple instances of same appliance. In order to detect an appliance in the presence of multiple appliances, more complex appliance features, extracted from better machine learning techniques may be needed. However, CM EMI will still serve as a useful signal for classification since CM EMI (unlike DM EMI) does not couple between multiple appliances. Therefore, this problem presents a unique opportunity for future research in this field.

VIII. ACKNOWLEDGEMENT

Authors acknowledge the support provided by ITRA project, under grant ITRA/15(57)/Mobile/HumanSense/01.

REFERENCES

1. Paul, C. R. *Introduction to electromagnetic compatibility*. John Wiley & Sons.
2. Gupta, S., Reynolds, M. S., & Patel, S. N. ElectriSense: single-point sensing using EMI for electrical event detection and classification in the home. In *Proceedings of the 12th ACM international conference on Ubiquitous computing*. ACM.
3. Gulati, M., Ram, S. S., & Singh, A. An in depth study into using EMI signatures for appliance identification. In *Proceedings of the 1st ACM Conference on Embedded Systems for Energy-Efficient Buildings*. ACM.