MagnoTricorder: What You Need To Do Before Leaving Home

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ABSTRACT
In this paper we present the design and the evaluation of a framework MagnoTricorder, a system that utilizes the magnetic sensor in smartphones to detect the running devices at home thru a single-point sensing. MagnoTricorder leverages the effect of Electro Magnetic Interference (EMI) generated by the AC current in the main power-line at home. This EMI induces a magnetic field that highly fluctuates the reading of the magnetic sensor in smartphones. In this paper, we utilize this characteristic for detecting and identifying the running devices at home thru the Circuit Breaker Panel. Experimental evaluation demonstrates the feasibility of the developed framework. Results show that MangoTricorder can detect and identify individual devices with 93%-98% accuracy.

1. INTRODUCTION
Smart Home is becoming a hot area of research for both academic and industrial researchers. Proliferation of smart devices such as smartphones, laptops, PCs, tablets, sensors, etc., accompanied with deployed wireless networks at homes open up the vision of having smart home as reality. In Smart Home, sensing the status of home devices (e.g., home appliances) is a corner stone for having better control over the home appliances as well as power consumption. In the rest of this paper, we use the term "device" to refer to any types of electrical device at home including home appliances, computing devices, non-computing devices, etc.

Industries have provided numbers of smart home applications to monitor and control the home devices using smartphones. However, these applications need expensive and cumbersome deployment and configuration of sensors and wireless networks [10, 1, 2, 3, 7, 8, 12, 6, 9]. Consequently, these applications become unattractive to users and become very limited in usage. On the other hand, nowadays smartphones come with a growing number of embedded sensors. Utilizing several of these sensors, such as magnetic sensor, light, microphone, temperature, camera, WiFi, in smartphones is becoming a new paradigm of research for smart home applications. In [13, 14], we proposed a platform to exploit the multiple sensing modalities of smartphones to detect the running devices at homes. In this work, as a proof of concept, we exploited the sound sensing capability of the smartphone to detect and monitor the running devices in user's vicinity. As a continuation of our efforts in building multi-sensing system, we explore and evaluate, in this paper, the feasibility of using the magnetic sensor in smartphones in detecting and identifying running devices thru a single-point sensing.

The magnetic sensing capability, as we will show later, allow us to develop several interesting applications for typical home usage scenarios. A very common usage scenario is checking whether any home device is on before leaving the house or the apartment. In this scenario, users are interested in checking on devices such as Heater/AC, kitchen oven/stove, microwave oven, lights, etc., that should be off while they are not home. Checking such devices before leaving home is important for both safety and power saving. In order to simplify this process, we are develop and evaluate a simple framework; MagnoTricoder that exploits the magnetic sensor in smartphones to detect and identify any running home device by using a single-point sensing. A typical example of MagnoTricoder application usage can be the following: Before leaving home, Bob wants to make sure all devices are turned off properly. Instead of checking all the home devices, Bob can run the MagnoTricorder application in his smartphone while he is holding it near the Circuit Breaker Panel (CBP) for a few seconds. As a result, the MagnoTricorder application will inform Bob about which home device is still on.

In summary, the contributions of this paper are as follow:

- *We introduce the idea of using the magnetic sensor in nowadays smartphones to detect the running devices at homes.*
- *We identify and address the challenges of using the smartphone's magnetic sensor in detecting devices.*
- *We design and evaluate a simple framework for smartphone application to detect and identify the running devices at homes using a single-point sensing.*

2. BACKGROUND AND OVERVIEW
In our previous work [13, 14], we proposed a multi-sensing system that exploits various sensing modalities in smartphones to build a unique fingerprint profile for each individual running device in order to detect, identify and monitor these devices. In building the fingerprint profiles, the characteristics of each device (e.g., sound characteristics, light characteristics, etc.) are collected and analyzed to identify the unique features and the corresponding sensors that could be used to detect and identify the device. As a proof of concept, we have exploited only the microphone sensor

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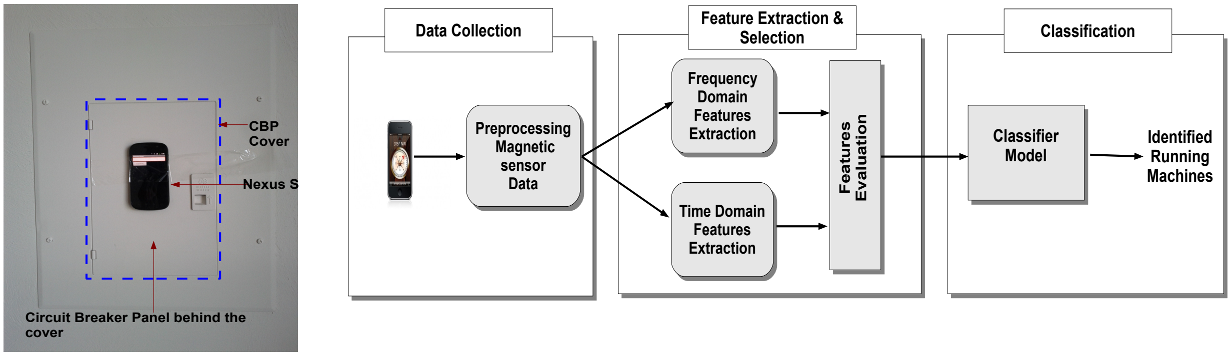


9(a) 9(b)

Figure 1: (a) Collecting magnetic sensor reading using Nexus S phone. (b) Operational block diagram of our smartphone application.

of the smartphones in building sound profile for each individual device. Unfortunately, sound sensing has several limitations. One significant limitation is that sound sensing is not able to detect devices that do not generate sound such as laptop, light, kitchen oven, etc. Another important limitation is the device proximity requirement for high detection accuracy. In this paper, we are aiming to overcome the sound sensing limitations by exploring and evaluating the magnetic sensing capability of the smartphones. The magnetic sensor of the smartphones measures the direction of the Earth's magnetic field that is typically utilized by the smartphone compass and navigation applications to determine directions.

In this paper, we develop a framework, MagnoTricorder that leverages the effect of Electro Magnetic Interference (EMI) that is generated by the AC current flowing thru the home main power-line. The flow of the conducting AC current in the main power-line depends mainly on the load of the running devices at home. The more the AC current flows in the main power-line, the higher the generated EMI around the power-line wire. This EMI induces a magnetic field that highly fluctuates the reading of the magnetic sensor in smartphones. One way to observe this phenomenon is by bringing the smartphone close to the CBP, the magnetic sensor readings start to fluctuate. The variation of this fluctuation depends on the type of running devices at home. Figure 2, shows how the magnetic sensor readings in Nexus S phone differs for different devices. In this paper, we utilize this phenomenon for detecting and identifying the running devices at home thru a single-point sensing; the CBP. The CBP has fairly common standard according to the National Electric Code (NEC) for all residential places in north america. The NEC, which is adapted by most buildings in USA, recommends to place the CBP in a clear, easily accessible and safe place inside the house. Placing the CBP at easily accessible area in the house (e.g., near the entrance) make it a suitable place of single-point sensing for detecting the operating devices before leaving home.

MagnoTricorder framework entails a number of research challenges. The first challenge is the use of a very narrow bandwidth low-pass filter to reduce the EMI effect of the surrounding environment on the magnetic sensor in order to have stable compass readings. More specifically, the narrow bandwidth low-pass filter makes the magnetic sensor in smartphones less sensitive to high frequency interference. Given the use of the high frequency (i.e., 60Hz) for the AC current in US, the magnetic sensor in smartphones is not sensible enough to detect the EMI effect around 60Hz frequency. The second challenge is the effect of the smartphone's orientation on the magnetic sensor reading. As shown later, it is important in the features selection component of MagnoTricorder to select orientation invariant features that are less sensitive to the smartphone's orientation. In this paper we have addressed these challenges and consolidate the implementation of our application.

3. MAGNOTRICODER FRAMEWORK

Figure 2(b) shows the main components of MagnoTricoder framework. The first component of the system is the Data Collection that is responsible to collect and preprocess the raw magnetic sensing data from the smartphone. Next, the processed data is fed to the Feature Extraction & Selection component in which we apply our feature extraction techniques to extract the useful set of features. Finally, in the Classification component, we apply training algorithms to build a classification model based on the extracted features from the training data. Using a collected testing data, we test and evaluate the developed classification model. In the following subsections, we describe in details each of these components.

3.1 Data Collection

In this paper, we use Nexus S phone for our data collection. Nexus S uses the AK8973 3-axis Magnetic field sensor chip. During the data collection period, we place the phone on top of the CBP surface as shown in figure 2(a). We collect the magnetic sensor readings along with the corresponding timestamps for over 3 days period. We change the orientation and the position of the phone on the surface of the CBP in each day so that we can analyze the effect of the orientation and the position of the phone on the detection accuracy.

We split the collected data to two sets; training data and testing data. The training data is used in developing and training the classification model, while the testing data is used to test and evaluate the model. In collecting the data, we start with turning off all the devices at home and get the magnetic sensor readings as the baseline load (no running device). Then, we turn the devices in sequence in order to collect the magnetic sensor readings for each device. We repeat this controlled experiment over each day to collect the magnetic sensing data for each device multiple times.

Over the three days period, we collected 15-20 minutes of the 3-axis magnetic sensor data in total for each individual running device with 118 samples per second. We collected the sensor data for the following scenarios: 1) Heater On, 2) Heater Paused, 3) Air

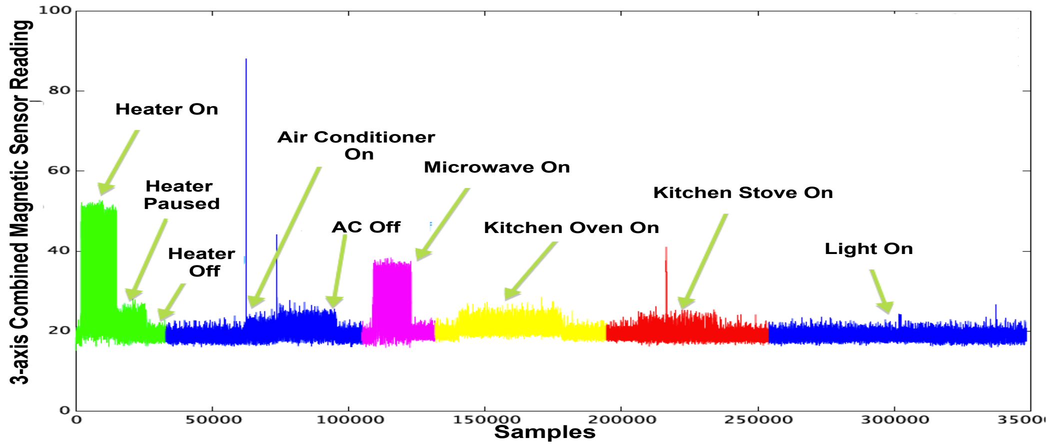


Figure 2: Magnetic sensor readings from Nexus S phone over a period of time. X-axis represents the number of samples over a continuous period of time. We have collected 118 samples per second. Y-axis represents the square root sum of three-axis magnetic sensor reading from Nexus S phone.

Conditioner On, 4) Oven On, 5) Microwave On, 6) Light On, 7) Laptop Charged (is plugged in the power socket), and 8) All Off (baseline load where no device is on).

3.2 Feature Extraction & Selection

In this component we have two main goals to achieve: i) the selected set of features should be able to differentiate between different devices with high success ratio, and ii) the selected set of features should not be sensitive to the smartphone's orientation. Our selected features consist of one time-domain feature and nine other frequency-domain features. In this section, we describe in details the steps we followed to extract and select the useful features from the processed magnetic sensor data.

Before extracting the features, we split the processed magnetic sensor data samples (training data) into a sequence of non-overlapped five-second periods. In this paper we refer to each five-second period of collected samples as an *epoch*. We apply our feature extraction process on each *epoch* to get the final set of features. For each *epoch*, we have a total of 118*5=590 samples in which each sample is a combination of the raw 3-axis magnetic sensor reading in the form of $\sqrt{x^2+y^2+z^2}$. Next, we calculate the samples mean and the variance for each *epoch*. Figure 3 shows how different machines are quite distinguishable with respect to the calculated means and the variances of multiple *epochs*.

By examining the calculated means, we found out that these values are highly dependent on both the orientation and the distance of the smartphone with respect to CBP. On the other hand, the variance values are not sensitive to the smartphone's orientation but sensitive to the distance to the CBP. The further we take the smartphone away from the CBP, the lower the variance values. In addition, we also observed that the actual position of the smartphone on CBP cover has some effects on the magnetic sensor readings. Although we only consider the position of the smartphone in this paper to be placed at the center of the CBP cover, we plan to study in future how the position of the smartphone affects the feature selection component. In this paper, we select the variance of the magnetic sensor readings as one of our potential features.

To explore other possible features, we apply the Fast Fourier Transform (FFT) on the samples of each *epoch* to get the frequency spectrum of the samples in the frequency domain. Figure 4(a) shows the power ($|FFT|^2$) values at different frequencies for different devices. From this figure, we observe that the power values at frequency 0Hz are quite large and distinguishable for different devices. The power values at 0Hz represent the DC power that have the same problem as the mean values (in time domain) that we have discussed earlier. The power value at 0Hz is highly sensitive to the orientation of the smartphone. Hence, we exclude the DC power values at 0Hz from our potential features set.

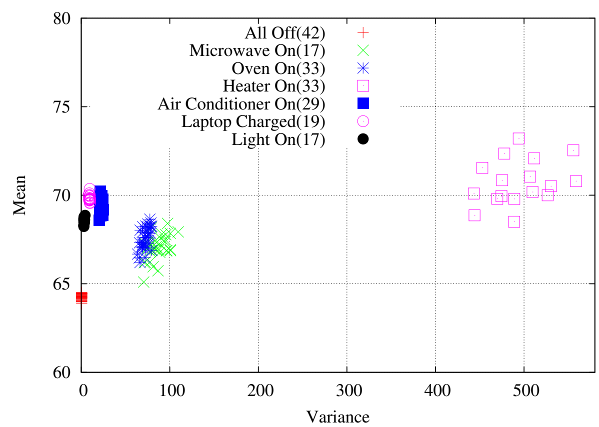


Figure 3: The mean and the variance values of the magnetic sensor readings for different devices.

In frequency domain, we have a total of 1024 frequency "bin" between 0Hz and 59Hz. Since the power values after 3.5Hz is negligible for all devices, we only consider the power values of the first 64 frequency bins (excluding the first bin corresponding to 0Hz) as our potential features. These 64 frequency bins (from 2 to 65) cover the frequency range 0-3.5Hz approximately. Figure 4(b) shows the power values corresponding to the 64 frequency bins for different devices. Figure 4(c) shows the Inverse FFT signal (IFFT) of the power values when applied to the 64 frequency bins. In this figure, each device shows a unique signal pattern even though we cutoff the higher frequencies as well as the DC power component of the frequency spectrum. Therefore, we consider these 64 power values of the frequency bins from 2 to 65 as potential features for further evaluation.

Finally, we rank the potential features by measuring their information gain with respect to the training data. In order to calculate the information gain, we calculate the entropy value of each feature for the whole training data. High entropy value indicates that the corresponding feature contains high information to differentiate between different devices. We select the top ten features based on the calculated gain values of these features. The selected ten features ordered based on their gain values are shown in table 1. Figure 5 shows how the training samples are spaced in 3D with respect to the top 3 selected features from that table.

Time Domain Features	Variance of the magnetic sensor reading in a window
Frequency Domain Features	Power values at Frequency bin 2,4,3,5,17,7,15,19,18

Table 1: Selected feature set for classification.

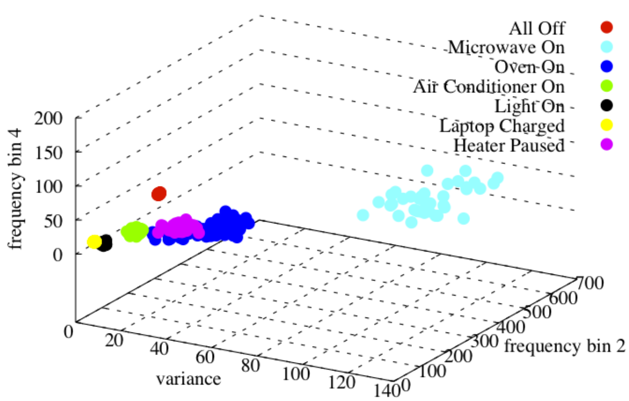


Figure 5: Scatter plot of all training data with respect to three features: Variance, Power at frequency bin 2, and Power at frequency bin 4. These 3 features have highest gain values compare to other features.

3.3 Classification

As we discussed earlier, we split the collected data over three days to two sets; training data and testing data. The data collected in the first two days is used as a training data to build the classification model, while the data collected in the third day is used as a testing data to evaluate the developed classifier. In training and testing the classification model, we use Weka Software [4] because it is very flexible in both analyzing the features and building the classifier model. In building the classification model, we select the classifier with low-complexity implementation of the training algorithm, such as Bayes Network, Naive Bayes, and K-nearest neighbor classifier. Table 2 shows the number of *epochs* of the training data and the testing data we use in classification. Table 3 shows the classification accuracy by using the testing data for different classification models. In this paper we use k=3 for the K-Nearest Neighbor classifier.

Scenarios	# training data	# testing data
All Off	64	30
Heater On	47	23
Heater Paused	32	11
Kitchen Oven On	67	21
Air Conditioner On	98	34
Microwave On	37	13
Light On	71	17
Laptop Charged	94	24

Table 2: Number of Training and Testing sample for different devices.

Algorithm	Accuracy
K-NN	95.38%
Bayes Network	98.27%
Naive Bayes	97.69%

Table 3: Classification accuracy using different algorithms.

In order to evaluate the robustness of our selected features, we evaluate different classification models built with different training data sets. In doing this, we use the data collected over one day as the training data and the data collected over the other two days as the testing data. Using round-robin fashion over all three days data collection, we get three different training and testing data sets. We use Bayes Network classifier to build three different classification models corresponding to the three training data sets. Table 4 shows the accuracy we have obtained over the three models. The high accuracy results of MagnoTricoder system in this table validates the robustness of the selected features regardless of the day used in building the classification model. In addition we observe that the accuracy results in Table 4 is quite the same as that of Table 3. Such observation indicates that our selected features are robust enough in terms of accuracy even if we use smaller size of training data.

1st day's data	2nd day's data	3rd day's data	accuracy
T	X	X	93.56%
X	T	X	97.07%
X	X	T	95.02%

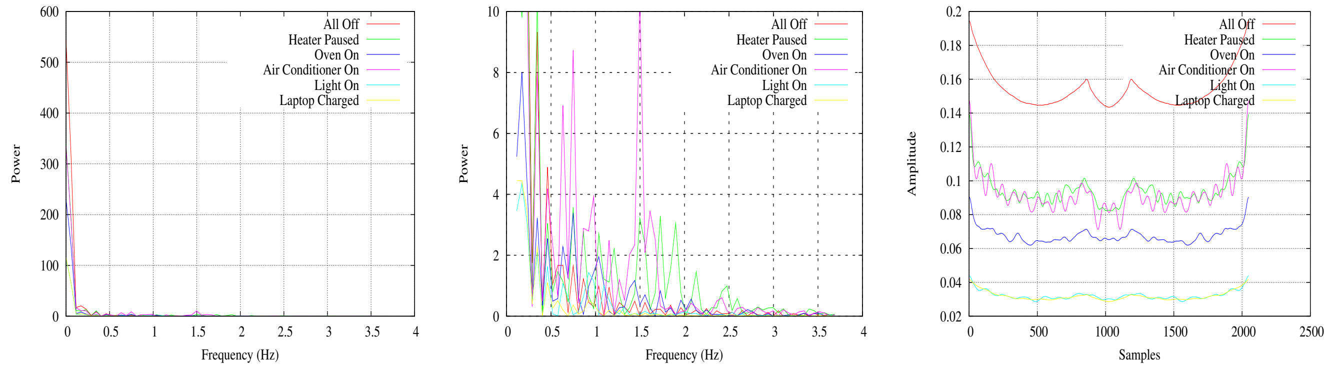
Table 4: In the table X = Data is used for testing and T = Data is used for training. Accuracy of detecting running devices under different scenarios.

4. PERFORMANCE EVALUATION AND DISCUSSION

In the following subsections, we evaluate the performance of MagnoTricoder framework under two main scenarios.

4.1 Different Days/Times Scenario

In this scenario we evaluate the accuracy of the proposed system with data collected on different days and times. In order to evaluate such scenario, we use the Bayes Network classification model that is build using the first two days training data as described in Section 3.3. Our testing data set is collected over another two days after two weeks period from the training data. In the first day, the testing data is collected at night between 8:00pm-8:30pm, while the testing data is collected in the second day at morning between 10:00am-10:30am. Table 5 shows the accuracy results of the new collected testing dataset. The equivalent accuracy in detecting devices over different days validates the robustness of



9(a) 9(b) 9(c)

Figure 4: (a) Power values of different devices for the frequency range 0-3.5Hz (b) Power values for the 64 frequency bins (from 2 to 65) for better visualization (c) Output of the IFFT when applied to the 64 frequency bins for different devices.

our system over different days/time. In addition, the high accuracy results in Table 5 indicates that the proposed system is consistent over long duration.

Day/Time	accuracy
First Day/ Night	93.56%
Second Day/Morning	97.07%

Table 5: Accuracy of determining running machines under different Days/Time.

4.2 Different Phones Scenario

In this section, we evaluate the performance of the developed system under the usage of different phones of the same model. In pervious analysis we have used the same phone for collecting both the training and the testing data. In this experiment, we use two Nexus S phones in which one phone is used to collect the training data while the other phone to collect the testing data. For classification, we use the Bayes Network classifier for detecting and identify running devices. Table 6 shows the confusion matrix for the collected testing dataset. Using 10-fold cross validation, we observe an overall average accuracy of 95% over our testing dataset. In the confusion matrix table 6, the accuracy of detecting *Heater Paused* event is low due to the fact that in our feature space the *Oven* event and the *Heater Paused* event are very much closer to each other. Figure 5 represents the fact that the features extracted from the *Heater Paused* event almost overlap with the features from the *Oven* event. Such circumstance generates classifier confusion between the two devices. As a result, we found in the confusion matrix that among the six *Heater Paused* event four of them were detected incorrectly.

	All Off	Heater On	Heater Paused	Oven On	Air Conditioner On	Microwave On	Light On	Laptop Charged
All Off	21	0	0	0	0	0	0	0
Heater On	0	12	0	0	0	0	0	0
Heater Paused	0	0	2	4	0	0	0	0
Oven On	0	0	1	8	0	0	0	0
Air Conditioner On	0	0	0	0	21	0	0	0
Microwave On	0	0	0	0	0	4	0	0
Light On	0	0	0	0	0	0	11	0
Laptop Charged	0	0	0	0	0	0	0	18

Table 6: Confusion matrix over the collected testing data from a different phone than the one used to collect the training data.

5. RELATED WORK

There are number of research works that have focused on detecting and monitoring the running devices. Monitoring the electric energy consumption at homes motivates most of these works. Researchers and industries have developed such real time energy monitoring systems for householders [10, 1, 2, 3, 7, 8, 12, 6, 9]. Typically, monitoring home energy consumption requires continuous sensing of the running devices. Unlike this typical requirement, our smartphone framework does not require such continuous sensing for the running devices. Our proposed framework uses CBP as a single-point sensing. Single-point sensing idea has been utilized by researchers in other previous works with main objectives to infer the total power usage of the house and to detect any electrical event[10],[9],[6]. In [10], authors proposed to attach a custom plug-in sensor to the main power-line at home to detect any electrical event. The attached sensor detects any electrical noise or abruption in power-line due to the switching of an electrical device or due to the noise created by certain devices while in operation. In that work, authors used the noise or abruption in power-line as a signature to detect the event of turning on or off a particular light, a television set or an electric stove. In this paper we utilize the noise in the magnetic sensor reading rather then directly using the electrical noise. The ElectricSense [6] system is an another example of single-point sensing. ElectricSense is based on the idea that most modern electronics use Switch Mode Power Supply (SMPS) that continuously generates high frequency electromagnetic interference (EMI) throughout home's power-line. In that paper, authors use this EMI as a signature to detect the event of a device or a machine. In [9], authors use a contactless power consumption sensor attached to the outside of home's circuit breaker panel to monitor the total power consumption of the house. The author leverages the technique of sensing the magnetic field that is induced by the 60Hz current in order to infer the total power consumption in real-time. However, all these system requires additional custom sensing hardware to be installed in the house's power line for continuous period of sensing. On the contrary, our purposed system doesn't require to setup any custom sensor for the house's power line. In addition, the objective and the context of our application are different from continuous monitoring of electric events at home as in the previous works.

Non-Intrusive Load Monitoring (NILM) is one of the state-of-art work in monitoring home devices for measuring power consumption. NILM is based on the idea that, each individual running device generates a distinctive signature on the power distribution system of the building. In [5], authors use several additional environmental sensors like light intensity, temperature, acceleration and sound level with the NILM system to enhance the signature of the devices. In their work, they relate the power distribution event with the environmental sensing data to extract the relevant device-related information from the sensors. In [8], ViridiScope is a power monitoring system for individual devices at home, which uses magnetic, acoustic and light sensor to compute the consuming energy of the devices. The VirdiScope system collects the sensing reading by putting sensor devices near the device. In [11], the authors use radio frequency to identify non-WiFi devices like, microwave, video camera, cordless phone etc. Inferring from the article [11], radio frequency can be a potential way to identify very specific running devices. Again, all these schemes require the installation of additional sensing hardware.

6. CONCLUSION AND FUTURE WORK

In this paper, we evaluate the feasibility of using the magnetic sensor in smartphones to detect the running devices at home by using the Circuit Breaker Panel (CBP) as a single-point sensing. The proposed framework utilizes the effects of the conducting AC current over the magnetic sensor in smartphones. Performance evaluation of the experiments and the corresponding results show that this approach is feasible and promising. However, there are some challenges in using the smartphone's magnetic sensor in detecting devices using the CBP. For example, we have noticed that the further the smartphone is placed from the CBP, the less sensitive the magnetic sensor becomes in detecting devices. The system generates the best accuracy when the phone is placed on the CBP cover as shown in Figure 2(a). This behavior is due to the low sensitivity of the magnetic sensor in Nexus S phone. In addition, the position we hold the phone at the CBP cover affects the detection accuracy. In future, we plan to investigate more about this issue. Another challenge is that the magnetic sensor chip in Nexus S phones uses a very narrow bandwidth low-pass filter in order to reduce the electromagnetic interference effect from the surround environment. This feature prevents the designed framework from utilizing the high frequency features that might improve the detection accuracy. In addition, further analysis of our framework is needed under more complex scenarios. As future work, we plan to focus on the following complex scenarios:

- **Detecting multiple running devices**: In this scenario, we will explore how to detect multiple running devices at the same time using the single-point sensing idea. While two or more devices are on, the AC current in the main power-line is expected to be higher than the AC current for each individual machine. The question is whether this aggregated AC current is a linear function of the individual device's AC current. If not, then what type of function it is. In addition, we need to evaluate the relationship between the increase in the AC current and the fluctuation of the magnetic sensor readings.

- **Position of the Smartphone on the CBP cover**: We have seen that the position of the smartphone on the CBP cover has some effects on the collected sensor data. We would like to explore how the data sensed for a particular device is changing with the position of the smartphone on the CBP cover. The typical architecture of the CBP is consistent among different residential homes. So we are expecting to have common behavior of the sensing data for holding the smartphone at different positions at the CBP. In future we like to analyze this scenario in more details.

- **Evaluating Different Phone models**: In this paper we have evaluated our system with different phones of the same model (i.e., Nexus S). In future, we will explore how our system performs using different phone models. Usually, different phone models use different manufactured magnetic sensor chips. It is more likely that the effect of EMI will vary with different magnetic sensor chips. Therefore, it is important to understand how to modify the proposed framework to support different magnetic sensor chips in order to detect and identify running devices at home wit high accuracy.

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