

MagnifiSense: Inferring Device Interaction using Wrist-Worn Passive Magneto-Inductive Sensors

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ABSTRACT

The different electronic devices we use on a daily basis produce distinct electromagnetic radiation due to differences in their underlying electrical components. We present MagnifiSense, a low-power wearable system that uses three passive magneto-inductive sensors and a minimal ADC setup to identify the device a person is operating. MagnifiSense achieves this by analyzing near-field electromagnetic radiation from common components such as the motors, rectifiers, and modulators. We conducted a staged, in-the-wild evaluation where an instrumented participant used a set of devices in a variety of settings in the home such as cooking and outdoors such as commuting in a vehicle. MagnifiSense achieves a classification accuracy of 82.6% using a model-agnostic classifier and 94.0% using a model-specific classifier. In a 24-hour naturalistic deployment, MagnifiSense correctly identified 25 of the total 29 events, while achieving a low false positive rate of 0.65% during 20.5 hours of non-activity.

Author Keywords

Sensor, Magnetic, Activity Recognition, Wearable Device

ACM Classification Keywords

H.5.m Information interfaces and presentation (e.g., HCI): Miscellaneous.

INTRODUCTION

Knowing what devices or appliances a person operates is important in many ubiquitous computing applications, such as personalized energy disaggregation, activity tracking, and adaptive user interfaces. For example, a cookbook application can preload and progress automatically when a user begins cooking. In a nursing home, tracking an individual elder's pattern throughout the day can help caregivers monitor each person's activity [27, 29].

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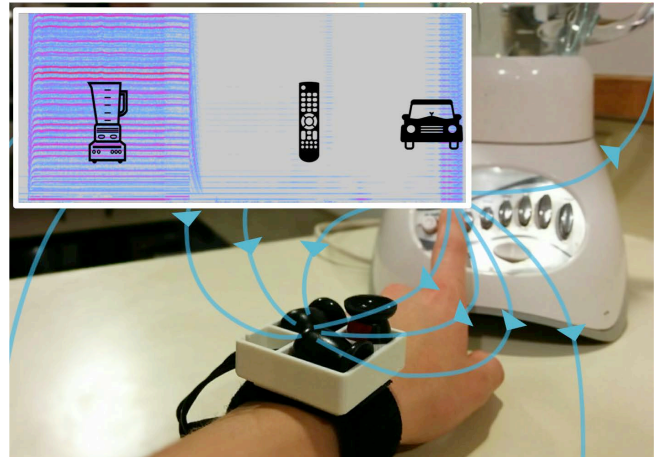


Figure 1: MagnifiSense is a wrist-worn magnetic radiation sensing system that detects and classifies the electrical device a person is using based on the unique radiated EMI signature of different electronic components.

A potential way to track someone's activity throughout the day is to analyze which electronic devices they are using in their environment. By sensing the electronics being used, a system could infer their current activity (e.g., stove implies cooking, car implies commuting).

In this paper, we present MagnifiSense: a user-worn magnetic sensing system that captures near-field electromagnetic interference (EMI) produced by electronic devices to track user-specific device interaction and usage. An important advantage of this wearable solution is that it is both user-specific and does not require specially instrumented environments. By using the radiated EM signal inherent to many appliances and devices, no modifications are needed to the devices either.

We present an investigation of EM radiation frequencies for activity tracking through the use of off-the-shelf, low-cost magneto-inductive sensors that use inductors – coils of wire wound around permanent magnets. These simple sensors are passive, and hence very low-powered in comparison to magnetometers or magneto-resistive sensors. More importantly, these sensors capture a broad frequency response that extends to the MHz range. This wide spectrum allows the system to differentiate the unique

radiation of various electronic components ranging from motors, rectifiers, and many forms of modulators. These radiation patterns are a byproduct of how the circuitry inside consumer electronic devices operate – particularly, how the current consumption can vary significantly from one device to another. Using domain knowledge in the physical circuitry of these devices, MagnifiSense is capable of differentiating between various devices.

We evaluated MagnifiSense in a controlled naturalistic study across 16 homes and 12 different devices, covering standard plug-in devices, battery-powered devices, and vehicles. In this study, we recorded 460 minutes with a total of 240 events. MagnifiSense achieved 95% event detection accuracy and 82.6% classification accuracy when using a device-model-agnostic classifier and 93.5% when the training data for that particular make and model of the device was included. This would be a comparison of a factory calibration versus a personal calibration. To further verify the robustness of the event detection algorithm against ambient noise, the system was deployed in a long-term study for 24 hours in a natural living environment. The system correctly identified 25 of the 29 automatically annotated events and only resulted in 7.4 minute of false positive detections, *i.e.*, 0.65% of the 20.5 hours of no device activity.

RELATED WORK

Activity tracking systems either involve instrumenting the environment or instrumenting the user. Instrumenting the environment avoids burdening the user with equipment, but often comes with installation costs or loss in information (*e.g.*, user association). Instrumenting the user requires that the technique balances between not being too power intensive for continuous sensing and also providing enough information for activity tracking in order to be feasible on a mobile platform.

Instrumenting the Environment

Researchers have explored various technologies to achieve in-home activity detection, including measuring device electrical loads, vision-based tracking, and device tagging.

By tracking the load drawn by each device, it would be possible to identify the device being used in the home. Currently, commercially available solutions for in-home device load monitoring require a power sensor to be installed on every device [5, 24]. Such solutions are often critiqued for their expensive installation and maintenance costs, both monetary and effort-based. To combat the issue of installing a sensor on every device, single point sensing approaches called Non-Intrusive Load Monitoring (NILM) have arisen [4, 7, 9, 19]. These approaches disseminate device usage by analyzing the current and voltage of the total load at the device’s interface to the power source. The main disadvantage of load monitoring systems is the inability to identify the actual user of the device, thus motivating systems that instrument individuals with sensors to disambiguate who performed the activity [22].

Furthermore, NILM systems inherently cannot detect devices that are not connected to the instrumented environment, such as battery-operated devices and vehicles.

In contrast, vision-based tracking attempts to identify device usage with strategically placed cameras installed in the environment to identify the devices being used [20]. Unlike load monitoring techniques, vision-based tracking could potentially identify the user through various facial recognition techniques. However, the installation of such a system is not easily scalable and presents privacy concerns.

To provide both activity and user identification, wrist-worn RFID readers have been used to detect RFID-tagged devices [23]. This technique benefits from a high signal-to-noise ratio since the RFID reader can be tuned to detect only nearby objects. Furthermore, this technique is also useful in identifying non-electronic objects such as chopping boards, toilets, doorknobs, *etc.* However, such systems suffer from high installation costs and do not detect when a device is actually turned on, just that the device is close to the user.

Instrumented Individual

The main disadvantages of environmental instrumentation are the inability to identify who is using the device and the installation cost. Instrumenting the user is a more direct way of identifying who is using the device, provided the assumption that there is a one-to-one mapping between the instrumentation and the user. Techniques in this category primarily include vision, acoustics, and motion tracking. Vision techniques are similar to their sibling systems in the instrumented environment category; instead of the camera being fixed in the environment, the user wears the camera [20]. Because the camera is mobile, attaining a clear line-of-sight is often difficult.

Acoustic systems attempt to identify devices by the sounds they produce. These techniques thrive when identifying motor-based devices, which produce varying acoustic signatures based on the mechanical system [8]. However, these systems are ineffective for devices that do not produce sound, such as stoves, lights, and remote controllers. Furthermore, sound-producing devices can likely be detected by anyone wearing the system in close proximity. Thus, if a blender were turned on in the kitchen, anyone in the kitchen could be identified as the person operating it.

User motion can also be leveraged to identify device usage. Turning a knob, using a blow dryer, and flicking a switch are all distinct motions that can relate to a particular device [2, 16, 18]. Sensing motion and vibration avoids the same-room confusion that audio systems can suffer from, but the general noise from everyday movement makes such systems impractical outside of controlled laboratory experiments. Motion has, however, found success in identifying the user’s mode of transportation. These techniques typically involve the fusion of motion data and

GPS signal traces to identify vibration and traveling speed patterns distinct to particular vehicles [10].

Magnetic Sensing

Various works have used magnetic sensors at the residential breaker panel to measure the magnetic radiation due to the current draw incurred by device usage [19, 25]. More similar to our approach, variants of such work have explored the radiated EMI from the device rather than the induced magnetic field from the current draw on the power line. Rowe *et al.* use a wrist-worn induction coil to measure the large magnetic flux produced by light switches [22]. Vaucelle *et al.* built a wrist-worn EMI detector that could sense nearby electronics such as PC monitors [26]. These work show the feasibility of using EMI radiation for detecting nearby operating devices.

Zhang *et al.* [28] performed a preliminary study that explored the use of magnetic sensors to distinguish between devices. They explored five different devices: computers, hair dryers, microwaves, cellphones, and televisions using their magnetic field strength. The advantage of measuring the radiated EMI at the device is being location and power source agnostic. Devices that run on a battery being used outside of the house still radiate EMI, but do not produce a signal at the breaker panel. Zhang *et al.*'s work shows the feasibility of classifying devices using radiated EMI, but their work was limited by the sampling rate of their magnetic sensor and could only distinguish devices based on power levels and variations. These works show the feasibility of measuring radiated EMI for activity tracking and presents an opportunity to explore a larger frequency bandwidth to make magnetic sensing for activity tracking more scalable.

Beyond devices commonly found at home, EMI is also produced from different vehicles. Magnetic sensors are already used by mechanics to identify engine misfiring and other abnormal behaviors. In fact, the signal is so strong that it may be sensed while sitting inside the vehicle. Manufacturers for in-vehicle navigation must be conscious of this magnetic noise in their compass design to ensure that the compass is able to detect the Earth's true magnetic north [12, 15]. Railway systems must take similar precautions since their large power controllers cover a wide spectrum of magnetic frequency bands. Instead of compensating for the magnetic signal generated by the alternators and internal circuitry of vehicles, MagnifiSense uses the same signal for identifying the user's mode of transportation.

DESIGN OF MAGNIFISENSE

MagnifiSense is a wearable system that uses three magneto-inductive sensors to capture the electromagnetic radiation of electronic devices. By using magneto-inductive sensors, MagnifiSense is able to perform in-depth power source distortion analysis previously not available to other mobile, magnetic sensing techniques. The prototype data acquisition system uses a multi-channel audio card with a laptop. In the following section, we will describe the

considerations that were taken to arrive at the final hardware setup. We then provide an in-depth overview of the signal characteristics that informed our signal processing and machine-learning algorithm. Finally, we detail the algorithms employed to perform the necessary event detection and classification.

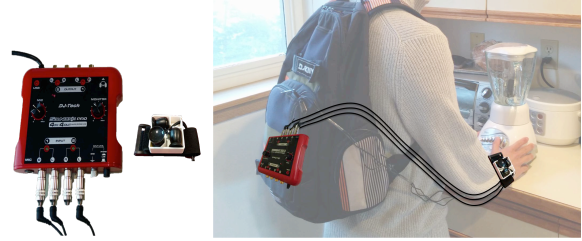


Figure 2: The data acquisition setup includes one 4-channel external sound card (Soundbox Pro 4x4) and three orthogonally placed magneto-inductive coil sensors (RS#07C12), each sampled with 16 bits resolution at 44.1kHz.

Hardware Development & Pilot Study

The MagnifiSense hardware system includes magnetic sensors and a data acquisition device. After a review of related literature, we identified three candidates for magnetic sensors – magneto-resistive, Hall effect, and magneto-inductive – and two main categories of data acquisition methods – regular analog to digital converter (ADC) and software define radio (SDR).

Sensor Options

Three types of magnetic sensors were considered: magneto-resistive, Hall effect, and magneto-induction sensors. Magneto-resistive sensors are power hungry due to the need for a relatively high (tens of mV) reference voltage that is constantly supplied to the offset strap. Hall effect sensors are the standard sensor type found in magnetometers for mobile compasses. The sensor requires only a few mV to sense magnetic fields, making it ideal for the low-power compass application. However, although some versions of Hall-effect sensors have sensitivity ranges of 100kHz, the typical range of sensors that are sensitive enough to the signals of interest are only 50Hz. Lastly, magneto-inductive sensors are passive sensors since the coil of the inductor induces a measurable voltage in response to a change in the magnetic field, also known as magnetic flux, and have sensitivity range in the MHz range. However, since the sensors only react to magnetic flux, these sensors cannot be used for static magnetic field measurements needed for a compass. For our system, all the signals of interest are AC in nature, and thus a magnetic flux sensor can be used the same way a magnetic field sensor can be used.

We chose the magneto-inductive sensor for our system because apart from having a large frequency response, it is also completely passive. We chose to use an off-the-shelf magneto-inductive sensor from RadioShack (model number RS#07C12), with a measured inductance of $250\mu\text{H}$. In its construction, a magneto-inductive sensor is a coil of wire around a magnetic core that takes advantage of the

induction of a voltage across the coil due to a change in magnetic field. This phenomenon is characterized by Faraday’s law:

$$V = -N \left(\frac{\Delta(BA)}{\Delta t} \right) = N \frac{d\phi}{dt} \quad (1)$$

where B is the magnetic field on the sensor, N is the number of loops in the coil, and A is the area of the loops under the magnetic field. The magnetic radiation captured by MagnifiSense is an induced magnetic field due to the electrical currents used by electronic devices. This phenomenon is described by Ampère’s law of magnetic field of current:

$$B = \frac{\mu_0 I}{2\pi r} \quad (2)$$

where B is the magnetic field around the current carrying wire, μ_0 is the permeability of free space, I is the current on the wire, and r is the distance from the wire. However, this model is only relevant when r is small (*i.e.*, a few centimeters). As the magnetic field enters near-field propagation regions, the strength attenuates at $1/r^6$ (-60dB per decade) [6]. This sharp attenuation of field strength motivates the relation between magnetic field detection to user interaction identification.

Data Acquisition Options

Two types of data acquisition methods were considered in the design of the system: regular ADC and SDR. An ADC simply converts analog signals from the sensors to a digital format. However, ADCs are typically limited to under approximately 1 MHz. To record higher frequencies, an SDR can repurpose 1 MHz bandwidth of an ADC to a higher frequency baseband, say 3 MHz, to acquire the signal between 2.5 MHz to 3.5 MHz. The use of a SDR would be similar in nature to Gupta *et al.*’s NILM technique, ElectriSense, but with an antenna rather than a direct connection to the power line. A quick survey showed that beyond the MHz range, most of the signals of interest would be from wirelessly coupled RF signal, such as from radio stations or local HF radio source.

To choose the ADC required for our system, we iterated through a pilot study and multiple improvements. The pilot study was a broad search across a multitude of devices and environments for three main purposes: (1) to identify the signal range of different home devices and appliances, (2) to verify that the signals of interest were actually magnetic and not capacitively coupled through the wire connecting the sensor to the data acquisition, and (3) to choose a list of devices for our prototype development. We examined the 33 devices listed in Table 1.

Space	Devices
Kitchen	Blender , mixer, food processor, food disposal, hood fan, microwave , <u>fridge</u> , resistive /gas/IR stove
Living Room	Laptop , <i>wireless mouse</i> , Incandescent/ <i>compact fluorescent</i> / dimmer lights, heater, TV remote , <u>vacuum</u>
Bathroom	Hairdryer , toothbrush , shaver , <u>vent fan</u>
Commute	Gasoline /diesel/hybrid/electric car, train, bus, plane
Others	Drills, elevator, overhead power lines

Table 1: The entire list of devices tested. The bolded devices were chosen for further evaluation. The italicized devices did not produce observable magnetic radiation. The underlined devices produced observable signal but was inconsistent due to the placement of the signal-producing component.

The acquisition system used in this exploration is the NI-DAQ 6259, which can collect 1 million samples per second. Two configurations were examined. The first involved one sensor using the entire 1 million samples per second. In the second configuration, three sensors were placed in the pocket and three sensors were placed on the wrist along with a single wire to capture the surrounding capacitively coupled noise.

We took away the following observations:

1. A 20 kHz sampling rate would be sufficient to capture most of the observable magnetic phenomena, excluding the high frequency wireless communication protocol of the mouse, for which the SDR would have been necessary. The IR communication of TV remotes is also slightly too high, at 37kHz, but we found that the signal was detectable through aliasing to the lower bandwidth [21].
2. The only capacitively coupled signal we encountered was generated from compact fluorescent bulbs, which create a broadband radiated electric wave; the rest of the signals were sampled magnetically. We account for this capacitively coupled signal in our noise model.
3. A few appliances, namely the fridge, vacuum, and bathroom fan, were not consistently observable because their signal source is often too far away from the user. This was also true for the TV remote, the laptop, and the bus, but for these devices, we found that the signal was observable most of the time depending on the position of the user’s wrist.
4. The near-field nature of magnetic signal made the wrist a very attractive instrumentation point.
5. The induced voltage measured at the wrist ranged from 0.5 mV to 500 mV, with the lowest signal being from TV remotes. The baseline noise tended to be around 0.3 to 0.5 mV.
6. Although the outdoor power line is not a personal device, it was observable when the user walked close to it outdoors. The signal was especially obvious when the user was close to the train stations and walking through dense neighborhoods.

Through the pilot study, it was clear that a regular audio card would provide sufficient sampling rate and the signal transduced by the passive coils are strong enough without amplification using typical resolutions. The final acquisition system uses a 16 bits, 44.1kHz external line-in audio card (Soundbox Pro 4-channel external audio card) to sample three passive RS#07C12 coils placed orthogonally on the wrist. The 12 devices examined in the later studies are enumerated in Table 2.

Cooking	Bathroom	Living Room	Outdoor
(1) Microwave	(4) Hair Dryer	(7) Dimmer	(10) Car
(2) Stove	(5) Shaver	(8) Remote	(11) Bus
(3) Blender	(6) Toothbrush	(9) Laptop	(12) Train

Table 2: After testing 33 types of devices, 12 of the most commonly found devices were chosen for evaluation to cover a diverse set of electronic components and contextual locations.

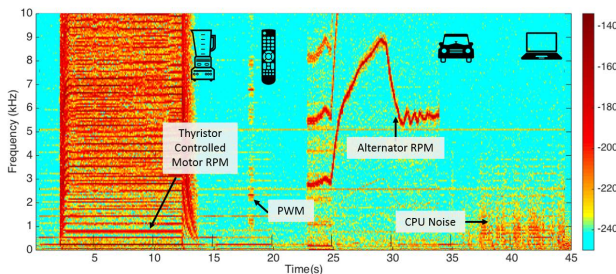


Figure 3: EMI radiation patterns of commonly found electronic devices depend on the underlying electronic component.

ALGORITHM DEVELOPMENT

We will discuss our algorithm development in two parts: signal source characteristics and implementation. The signal source subsection breaks down the magnetic characteristics of common electronics and provides an intuition behind the algorithm we ultimately implemented. The implementation subsection describes the algorithm pipeline and the features used for the event detection and classification algorithms.

Signal Characteristics

The classification algorithm was developed to incorporate analysis of common phenomenon that can be observed in electronic devices [1, 11, 13, 17]. Modern electronics non-linearly load the AC power supply, which creates distinct harmonic distributions depending on their operation. For DC systems, non-linear loading is introduced through control schemes such as pulse-width modulation, which can be found in motor speed controls or devices that communicate via IR LEDs. Finally, motors exhibit EMI radiation at the frequency of their rotation.

Signal Characteristics: Harmonic Distortion

The electricity that reaches the home runs at 50 or 60 Hz, depending on the standard of the country. Normally, both

the current and voltage are sinusoidal; however, harmonic currents are created when this power is fed into a non-linear load. A load is non-linear when the current draw does not match the supply voltage waveform. The harmonic current then flows through the system impedance, creating voltage harmonics, in turn distorting the supply voltage [1]. The most typical non-linear electronic components in modern electronics are semiconductor components, in particular rectifier diodes and thyristors.

Rectifiers can be found in many home devices for converting AC voltage to DC voltage. Rectification diodes convert AC power to DC power by only letting the current through the forward bias direction, with the forward current and voltage characteristic being non-linear as well. The current waveform for a single-phase full-wave rectifier system will be periodic with the AC supply voltage, but with a pulse-like signature close to the peaks of each half cycle (Figure 4).

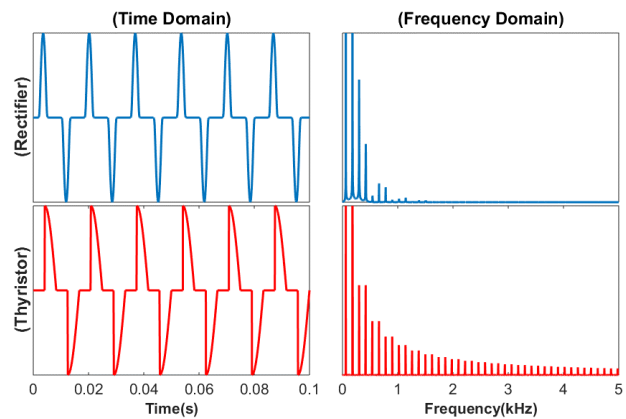


Figure 4: Full-wave rectifiers create pulse-like current at the peaks in the AC cycle due to the nonlinear I-V properties. TRIAC, a thyristor configuration, creates chopped AC waveforms as they only allow current flow at defined points in the phase. The chopped waveform of a thyristor results in many more harmonics in the frequency domain.

Thyristors are used to control the power delivered to devices, which is particularly important for controlling the speed of AC motors and the brightness of lights. A thyristor is a generic name for a semiconductor switch similar to diodes in that they let current through one direction, but can control when current is let through in the AC cycle. Thyristors are capable of controlling this timing with a scheme called phase-controlled firing. This control scheme is used to clip out segments of the AC power waveform to control brightness; the more the waveform is chopped, the slower the motor or dimmer the lights. The AC power is let through when a trigger is fired to the thyristor. This trigger is phase offset to the AC supply by means of a variable RC circuit. With a larger phase offset, the trigger comes later, thus clipping more AC power out and reducing the power delivered. Some configurations of the thyristor are DIACs, commonly used to produce trigger-like pulses, and

TRIACs, which allow bidirectional current flow, often used in dimmers (Figure 4).

From a signal processing perspective, the frequency characteristics of a rectifier and thyristor differ in the number of higher order harmonics. Because thyristors have a chopped waveform, the highly non-sinusoidal shape creates hundreds to thousands of higher order harmonics whereas a rectifier creates tens of higher order harmonics.

Signal Characteristics: DC Modulation

PWM is used to control the amount of DC power that is delivered to a motor or LED light. For a DC motor, controlling the power level will adjust the speed of rotation for a motor or the brightness of a light. By supplying a lower voltage, the speed and brightness will decrease. However, converting voltages down in a continuous fashion is impractical. PWM achieves the same effect by only supplying power for partial durations, alternating between on/off in a pulse train fashion.

This pulsing technique has also been used for IR communication. In remotes such as for TV, home media, and air conditioners, an IR transmitter transmits to an IR receiver by pulsing an IR LED at a known frequency and duty cycle. That frequency is commonly 37 kHz, but can change depending on the manufacturer.

Signal Characteristics: Rotary Machines

When a motor is turned on, brushes on either side induce polarity on multiple electromagnets arranged in a circle. As the flow of current changes directions, the polarity of these electromagnets flips. The induced poles then attract or repel the electromagnets, creating the motor's rotation. The flipping of the electromagnets creates an observable magnetic flux at the rotational frequency of the motor multiplied by the number of poles it has. Furthermore, the mechanical contacting of the brushes create notch-like waveforms, thus introducing harmonic distortions at integer multiples of the rotational frequency.

ALGORITHM IMPLEMENTATION

The algorithm of MagnifiSense follows a pipeline of (1) signal preprocessing, (2) event detection, (3) feature extraction, and (4) event classification. A sliding window of one second, with a step size of 0.5 seconds across the EMI data from the magneto-inductive coils is used for the event detection stage. Event detection is a low computation step based on a global threshold on the energy of the raw signal. Once an event is detected, a set of features based on the physical model described in the signal source section is generated. Finally, the features are used in a random forest classifier to produce a classification and a confidence. A confidence-based voting using a fixed window size is used to determine if the event detected is recognized as a device, noise, or unknown device.

Signal Pre-Processing

Before any analysis is performed, the energies of the three channels are combined in the frequency domain. This

entails applying the Fourier Transform on the three channels and summing the magnitude of the frequency bins. It is important to note that by combining the three channels, the system becomes orientation agnostic. Second, a filter removes the baseline system characteristics of the data acquisition system, which in our case were oscillator signals that originated from the computer and the internal timing circuitry of the audio card.

Event Detection

The event detection stage is designed to be low computation so it can be ran continuously on a one second buffer every half a second. The energy of the merged signal is computed over the buffer. A threshold produced by our noise model is then applied. If the energy is above the threshold, the buffer is then analyzed for classification.

The global threshold is tuned for a high true positive rate at the cost of a higher false positives rate. In our parameter tuning with our training data, we chose a detection threshold that gave a 97.5% true positive rate and a 7.2% false positive rate. This allows us to have minimal loss in detecting the existence of a signal, and on the off chance that the ambient noise rises above the typical noise level (e.g. passing a light pole on the streets), the system can then rely on the classifier to identify real events versus null events.

Event Classification

After an event is detected, a set of features is computed on the one-second buffer for classification. The classification can either result in high confidence, which will be recorded, or low confidence, which will be considered an unknown event and ignored.

Event Classification: Feature Extraction

Each one-second buffer is transformed into a feature vector of 49 features informed by the signal characteristics described above. The following section will go into further detail about the features and intuition behind them.

Fourier Transform Features

- **Power of frequency bands:** The power of the low (0 to 1kHz), medium, (1kHz to 10kHz), and high (>10kHz) frequency bands are recorded. The power is then normalized over the total power of the signal. Most of the non-motorized electronics operate at the low frequency band (stoves and microwaves). Most of the motorized systems have frequency content in the low to medium range. Some highly non-linear systems like dimmers, trains, and some brands of toothbrushes leech over to the high frequency bands.
- **Harmonics of the AC supply:** The first 10 harmonics of the AC supply bin are recorded to analyze the non-linear loading on the AC supply. The features generated include: (1) the ratio of even harmonic to odd harmonic magnitude (under 10^{th}), (2) the ratio of harmonic magnitude to the fundamental, and (3) the total harmonic energy. A high odd harmonic, arbitrarily

chosen as the 105th harmonic, is also used to capture the broadband frequency content of the dimmer's TRIAC waveform.

Short Time Fourier Transform (STFT) Features

The one-second EMI data buffer is further broken down into ten sub-frames to capture any short-term changes in frequency content, such as motor acceleration. The Fourier transform of each sub-frame was computed using a technique called the Short Time Fourier Transform.

- **Variance of the frequency distribution over time:** The frequency magnitude of the entire buffer was subtracted from the frequency magnitude of the sub-frames. This removes any stable signal over the one second, leaving only fluctuating signals. A high variance after subtracting out stable signals indicates fluctuating devices signals such as from motors.

Autocorrelation of Fourier Transform

The autocorrelation of the FFT is used to capture non-AC supply frequency harmonics created by pulse-width modulation and motor signals. These components result in repeated peaks at integer multiples of the fundamental or rotational frequencies. This is accomplished by taking the autocorrelation of the FFT after filtering the 60Hz harmonic bands. The resulting autocorrelation will amplify the repeating harmonic structures as peaks at the position of the fundamental frequency. Peaks are extracted by smoothing the signal, detrending to a mean of zero, and finally detecting zero-crossings. The following features were calculated based on this method:

- **Number of FFT autocorrelation peaks:** Motors tend to have five and twenty peaks in the FFT autocorrelation.
- **Decay of peaks:** The decay of the autocorrelation peaks shows the relative strength of the high-order harmonic peaks to the low-order harmonic peaks. High-order harmonic peaks are indicative of highly nonlinear components such as thyristors.

Autocorrelation of STFT

- **Peak analysis of the frame with highest energy:** The pulsating signal used for IR communication is bursty and lasts only about 100ms. The autocorrelation of the sub-frame with the pulses has the highest energy and show the frequency of the pulsed signal.

Event Classification: Classifier and Voting

The aforementioned features are used in a random forest classifier, which is well suited to capture the various states of operation within a single class of devices (start up, in use, change mode, turn off) [3]. It is unlikely that a device will only be used for one second (the size of the buffer for each classification). As such, multiple predictions are made for each event. An aggregated vote is made every 13 frames (6.5 seconds) in a continuous segment of detected events. The purpose of voting every 13 frames is to smooth out the prediction and catch any momentary events resulting in

isolated false positives. Equation 3 is the weighting function applied to the score of each vote based on the confidence of the classification from the RF classifier.

$$weight = \frac{1}{1.01 - confidence} \quad (3)$$

where the confidence is in the range of 0 to 1. This function puts a heavy reward for a high confidence prediction, while not penalizing too heavily for giving a lower confidence. A confidence of 0.5 is applied to all frames that were not marked as events for this calculation.

EVALUATION

The evaluation of the algorithm was performed in three stages: 1) controlled, 2) staged in-the-wild, 3) long-term naturalistic. The data collection was performed through the controlled study, where each device was measured for a few seconds at a time in multiple repetitions. The in-the-wild study was much looser, where the user was simply asked to walk around the house and use a set of devices as indicated on a script at their own pace. Finally, to evaluate the event detection system during naturalistic use, the system was deployed for 24 hours in a naturalistic environment where the user was asked to log their device usage.

Data Collection

We chose to examine the 12 different devices listed in Table 2. For each type of device, ten different instances were examined, each with ten trials, resulting in 100 trials for each device. Each trial included ten seconds of operation from turning on to turning off. A total of 16 homes were needed to complete 10 of each device.

For the bus and the train, data were collected by riding the vehicle for 11 consecutive stops, giving a total of 10 start stop events. Then, similar to the other devices in the study, ten samples for each vehicle were produced. In order to include different models of buses and trains, we collected data across two major cities that had two different rail systems and two different bus fleets.

Staged In-the-Wild Study

In order to evaluate MagnifiSense in a more realistic scenario, a scripted user study was conducted to gather continuous datasets while users interacted with various devices across their home. In this study, users carried a backpack holding the data collection unit and wore the 3-axis magnetic sensor package on their dominant wrist. Each user received a script asking them to use a series of devices they owned from our list of 12 in randomized order, repeating the sequence twice. All the devices were left where the user usually keeps them and the user simply walked around the house to use each device. The study was conducted with the same 16 users as the data collection. As it was difficult to include trains and buses in the same sequence, a separate study was conducted. For trains and buses, we recorded ten separate streams of continuous data. The collection was performed with about 3 minutes before entering the first bus or train. At the next stop, the user exits

the vehicle and waits for the next one. At the end of the second ride, the user exited the vehicle and another 3 minutes is recorded.

Long-Term Naturalistic Study

We performed one extended 24-hour naturalistic study with a single subject who carried the data collection system during their normal day. The study was broken into five sessions: four four-hour activity sessions (one outdoor + commute, one cooking + lounging + grooming, two working at a computer related job), and one eight-hour sleeping session. Over the course of the day, the user was asked to use each of the 12 devices at least twice. The subject was asked to limit the use of other devices throughout the sessions and to note any occurrences where this may have happened. During the sleep session, the subject placed the system by the bedside.

RESULTS & ANALYSIS

Controlled Study

The controlled study provided the dataset to train the random forest classifier. We performed two 8-fold cross-validations: across models of devices and not across models of devices. For across models, all the models included in each test fold is removed from the training fold. We refer to this as **model-agnostic**. When every trial is treated separately, we refer to it as **model-specific**. Model-agnostic would be similar to a factory calibration, while model-specific would be similar in nature to a calibration on personal devices. The confusion matrix in Table 3 is from the 8-fold cross-validation for the generalized model.

	(1) Microwave	(2) Stove	(3) Blender	(4) Hairdryer	(5) Shaver	(6) Toothbrush	(7) Dimmer	(8) TV Remote	(9) Laptop	(10) Car	(11) Bus	(12) Train
1	90	0	0	10	0	0	0	0	0	0	0	0
2	5	95	0	0	0	0	0	0	0	0	0	0
3	0	0	99	0	0	0	1	0	0	0	0	0
4	0	0	10	87	0	0	0	0	0	0	0	3
5	0	0	0	0	67	1	1	0	1	9	21	0
6	0	0	0	0	21	67	0	0	0	3	6	3
7	0	0	0	0	0	2	97	0	1	0	0	0
8	0	0	0	0	2	0	10	72	15	0	0	0
9	0	0	0	0	3	0	4	0	87	1	4	0
10	0	0	6	0	9	0	3	0	11	46	20	5
11	0	0	0	0	0	0	0	0	0	0	100	0
12	0	0	0	0	0	0	0	0	0	0	0	100

Table 3: The 8-fold cross-validation confusion matrix of the training data shows an average accuracy of 83.9%.

The model-agnostic classifier accuracy averaged 83.9% across 12 classes. Accuracy was particularly low for the battery-operated motors such as shavers (67%), toothbrush (67%), and the car (46%). However, the out of bag accuracy from the random forest classifier produced an accuracy of 99.8%, which in our case is the model-specific accuracy. The out of bag accuracy, being an unbiased estimate of the test set accuracy, along with the RF classifier being highly unlikely to be over fit, suggests that

there are potentially differences between brands of the same class that makes merging under the same class infeasible.

After further analysis of error distribution, we found that the errors were clumped to a few instances in a few classes, namely 3 toothbrushes, 3 shavers, and 4 cars. In these classes, if an instance was classified wrong for one trial, almost all of the other trials were also misclassified. On the other hand, the rest of the classes had errors spread throughout the various instances. This shows that for a subset of the devices, the model-agnostic features generalize consistently. With the subset of devices, after removing the toothbrush, the shaver, and the car, a 9-class classifier was retrained, with an accuracy of 91.9%.

Staged In-The-Wild Study

The staged in-the-wild study was designed to observe the signal in a more realistic setting. The dataset included a total of 460 minutes, of which 207 minutes were device activity spread across 240 individual events. The true positive rate of the event detection is the percentage of detected events out of the 240 events performed. The false positive rate is the percentage of minutes falsely detected as an appliance usage over the 253 minutes of inactivity. For the classification, the accuracy is presented for both model-agnostic/specific cross-validation models in Table 4.

Event Detection		
True Positive Rate	95.4%	
False Positive Rate	7.1%	
Classification		
# of Events	Model-Agnostic	Model-Specific
Detected (229)	82.6%	94.0%
All (240)	74.4%	89.9%

Table 4: The staged in-the-wild study produced 460 minutes (240 events) of data. The results are comparable to the controlled data set in both event detection and classification.

For the 240 events, the algorithm correctly segmented 229 events, giving a true positive rate of 95.4% after voting, and missed 2 TV remotes, 1 stove, and 8 laptop events. Of the 253 minutes of inactivity, there were a total of 14.4 minutes of events incorrectly classified as device usage, giving a false positive rate of 7.1%. The false positive events mainly classified to TV remotes (30%) and laptops (52%). Of the 95.4% of events detected, the classification accuracy averaged 82.6% for the model-agnostic classifier and 94% when the training set for the specific instance was trained. When the entire set of 240 events is considered, these accuracy results become 74.4% and 89.9%, respectively.

Long-Term Naturalistic Study

The long-term study totaled 24 hours of naturalistic data where a user wore the sensor across five session: four×four-hour daily activity sessions and one eight-hour sleep session. The dataset included 2.5 hours of active outdoor

activity (walking and riding a vehicle), 1.5 hours of low outdoor activity (waiting at bus station, sitting at a café), 11 hours of low indoor activities (laptop use, reading, sitting, watching TV), 3.5 hours of medium activity (cooking, eating, and grooming), and 8 hours of sleeping. The user noted a total of 29 contiguous events and no devices outside of the 12 listed in Table 2 were used.

A total of 3.5 hours of device interaction was recorded in total, although a large percentage of the activity time is from laptop use (1.5 hours) and commuting (1.5 hour). Of the 29 events throughout the day, MagnifiSense correctly identified 25 (86%) using the model-agnostic classifier. The algorithm detected 7.4 minutes of false positive results, or 0.65% of the entire 20.5 hours of no device interaction.

DISCUSSION

Controlled Study vs. Naturalistic Studies

The most notable result of the three studies was that the classification accuracy did not decrease with increased level of naturalistic device usage. This shows that the features based on the internal circuitry are invariant over time and location. In fact, the accuracy even increased in the 24-hour study. However, it should be noted that the accuracy for the subset of devices used in the 24-hour study was also high in the other two studies, so the increased accuracy was likely a result of not having poorly performing brands.

The false positive rate from the staged study was quite high, (7.1% of the total inactivity time); however, compared to the low false positive rate of 0.65% in a full 24-hour deployment where the user went more than 15 miles on a bus to catch a train, made dinner, and groomed for the morning, the high false positive of the staged study is likely overly pessimistic. We noted that in the staged study, the time of activity to inactivity is 1:1, whereas in the naturalistic setting the ratio was closer to 1:7. As such, the activity level of the staged study was much higher than natural, resulting in a noisier background.

Model-Agnostic vs. Model-Specific vs. Reduced-Model

There was a clear accuracy difference between the 82.6% of the model-agnostic classifier and the 94% of the model-specific classifier. In terms of real-world use, this would be a comparison between an out of the box calibration versus a one-time training of the user's personal devices. When the model-agnostic classifier is reduced to only devices that were clearly generalizable, the accuracy increased to 91.9%. This result shows that MagnifiSense can deliver a default factory calibration for globally generalizable devices and when the user interacts with devices that classify with low confidence, the system can adjust using manual labeling. Potentially, with a much larger system deployment, enough instances of every popular brand can be covered to eliminate the need for personal calibration.

LIMITATIONS & FUTURE WORK

Event Detection Sensitivity

The study results are very encouraging for the use of MagnifiSense to track everyday device usage, with a 95% true positive event detection rate. However, we did note a lack of sensitivity for the TV remote and the laptop. We attributed this to the varying signal strength depending on the hand placement. For the TV remote, the produced signal is a result of the current from the battery to the IR LED at the front of the device. Sometimes, the remote is either too short or the battery is placed too close to the front, making the already weak signal even weaker. For the laptop, we noticed that sometimes the user never actually placed their wrist over the laptop. This is especially true for smaller laptops, for people with large hands, and for people who use the trackpad. Furthermore, we found that the signal is strongest at different locations for different laptops (close to the screen for an Ultrabook and the bottom right corner for a MacBook Pro).

Compound Events

The current system is only meant to handle single events. This is usually a reasonable assumption because the system only detects a signal within close proximity (~1 m). However, in one of the events in the 24-hour study, the user happened to use a stove and microwave at the same time. The system correctly identified both events and flipped the prediction based on which signal was strongest, which presumably means the user moved between the stove and the microwave. However, for overlapping signals from different devices (e.g., dimmer and hairdryer), the system would need to employ more complex disaggregation techniques [14].

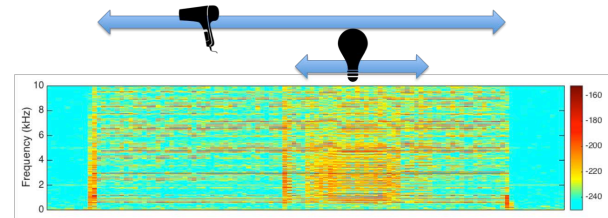


Figure 5: An example of a compound event where the dimmer signal overlaps a hairdryer signal.

Extension to Other Devices

Although we curated 12 devices for the evaluation, this is not a comprehensive list of all devices that we could detect. Of the 33 devices tested in the pilot, only four did not show promise with our hardware. The wireless devices would require an SDR in order to detect the signal in the MHz range. As for devices with distant signal sources, such as fridges and vacuums, a small $10\times$ amplification would be enough, but at the cost of making the sensor active.

Of the devices that were measurable, many were in the kitchen, especially those that include multispeed motors. This could be potentially worrisome for fine-grain device differentiation as the system scales, as many of these

motors are controlled using similar control schemes. A potential solution is to adjust the output from the classifier to group similar devices in the same space, such as grouping all multi-speed kitchen devices together.

Hardware Feasibility

As mentioned in the hardware development section, it should be noted that the coil sensor is completely passive. As such, a magneto-inductive sensor can easily be incorporated on-board a wearable device such as a smart watch without much more power. The space constraint on wearable devices may make placing three coils difficult. However, we noted that for most of the devices observed, even just one of the coils (typically the one facing the arm) was sufficient for capturing the signal.

Aside from reducing the number of coils, a different physical configuration of inductive sensors could be employed. The current sensor is about 1 cm in radius. Faraday's Law shows that output voltage is quadratic to the radius of the coil. As such, a coil of about 1 mm would be 100 times weaker, leading to a range of $5\mu V$ to $500\mu V$. This is still well within the resolution of commercially available ADCs, but with reduced sensitivity to weaker signals such as remotes, laptops, and some areas in the bus.

APPLICATIONS

The following section focuses on how MagnifiSense can augment existing technologies for higher activity recognition coverage and user identification, in particular for smart-home applications.

Multi-Occupancy Elder Home Care

In order to provide better care for those living in elder care homes, it is important to understand multiple occupants' daily activity. In this scenario, we might imagine each occupant would have a wrist-worn device with an inductive coil sensor and an embedded UHF RFID tag. Each device is connected with the elder home's centralized smart-home system, which also employs NILM to detect the appliances that are operating in the home. Proximity sensors are installed around the building to track if anyone is nearby.

In addition to providing better activity tracking, tracking who is interacting with a particular appliance provides an additional level of safety. For example, when the NILM system detects a stove is turned on, it can determine who had turned on a stove through MagnifiSense. With the proximity sensor near the stove, the smart home can determine when the stove is unattended. By knowing who is using the stove, a reminder could be sent to the person who was using it after they walk away for an extended period of time. This way, not only is there a sense of security of knowing that one will not forget about a potential fire, but also only the person who is actually responsible for the stove would be contacted. In the case when the person does not respond and the stove overheats, the RFID system could help determine who is closest to the stove and send an alert. Additionally, for portable appliances that are mobile like a

clothing iron, it might not be feasible to install proximity sensors. In this case, MagnifiSense can also be used to determine if anyone is actively using the device.

Furthermore, user identification can greatly improve the user experience of appliances that are shared amongst many people, such as a TV. With MagnifiSense, it is possible to tell who in the room actually used the remote to turn on the TV or switch the channel. This can be used to learn a user's behavior and preferences.

Interactive Smart Kitchen

MagnifiSense can also help create new kinds of user experiences. One of the most compelling smart home applications is a smart kitchen system that can help guide a home cook along a recipe. In-air gesture techniques could advance a user through a recipe without having to touch the computer. When multiple cooks are working together to make a complex recipe, each person might be working on a different part of the recipe, or maybe even two separate recipes. Using a wrist-worn inertial measurement unit (IMU) to detect motions like chopping or stirring, along with MagnifiSense to determine the appliance being used, it is possible to detect who is performing which part of the recipe. With the computer's built-in webcam, computer vision could be employed to determine who is looking at the recipe at any given time. Having determined who is performing which step, the correct part of the recipe could be advanced automatically as the recipe is being completed.

Personal Energy Footprint

MagnifiSense can be used in conjunction with NILM to help determine an individual's energy footprint around the home. It can also be used on its own while the person is out. Although not fully demonstrated in the evaluation, MagnifiSense shows promise in differentiating between different forms of transportation, such as cars, buses, trains, and planes. It can also determine many types of fuel systems such as gasoline, diesel, hybrid, and electric. The fidelity of the system can then be further improved using systems that employ vibration data and GPS coordinates to determine motion paths, which can help MagnifiSense improve its confidence in its classification over time.

CONCLUSION

The purpose of this paper is to demonstrate the amount of information available in the magnetic spectrum if we expand the sampling rate of the magnetic sensors in our mobile devices. In our exploration, we found MagnifiSense to be highly reliable in detecting device usage due to the relatively high SNR. It is important to note that the classification of devices was achievable because the expanded sampling rate allowed the different characteristics of electronic components to be resolved. Although current mobile systems cannot immediately employ MagnifiSense uncovers the value in introducing high sampling magnetic sensors into mobile systems because of its potential in providing high fidelity information to augmenting contextual awareness systems.

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