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A Home Security System Based on Smartphone Sensors

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A Home Security System Based on Smartphone Sensors

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Abstract

Several new smartphones are released every year. Many people upgrade to new phones, and their old phones are not put to any further use. In this paper, we explore the feasibility of using such retired smartphones and their on-board sensors to build a home security system. We observe that door-related events such as opening and closing have unique vibration signatures when compared to many types of environmental vibrational noise. These events can be captured by the accelerometer of a smartphone when the phone is mounted on a wall near a door. The rotation of a door can also be captured by the magnetometer of a smartphone when the phone is mounted on a door. We design machine learning and threshold-based methods to detect door opening events based on accelerometer and magnetometer data and build a prototype home security system that can detect door openings and notify the homeowner via email, SMS and phone calls upon break-in detection. To further augment our security system, we explore using the smartphone's built-in microphone to detect door and window openings across multiple doors and windows simultaneously. Experiments in a residential home show that the accelerometer-based detection can detect door open events with an accuracy higher than 98%, and magnetometer-based detection has 100% accuracy. By using the magnetometer method to automate the training phase of a neural network, we find that sound-based detection of door openings has an accuracy of 90% across multiple doors.

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I. INTRODUCTION

A. Overview

Mobile hardware is evolving at an extremely fast pace. Most big smartphone vendors produce a new smartphone every year, causing many users to upgrade to a new device every year or two. In particular, iPhone sales have nearly tripled in the last five years [1]. Most of these retired devices still function as expected save for some scratches or cracks, but are ignored until either recycled, sold at a fraction of the initial cost, or thrown away. This leads to the all-too-common "smartphone graveyard"- a place where old phones collect dust indefinitely. These retired smartphones are almost always equipped with highly sensitive motion capture chips. Though less frequently mentioned, these devices are also equipped with triple-axis magnetometers which are used for analyzing the device's orientation with respect to Earth's Magnetic North Pole. And, of course, these phones are all equipped with microphones.

Personal, small-scale home security systems are becoming increasingly popular. Most professional systems, however, cannot be installed by the end-user and come with a large upfront cost as well as recurring costs such as annual fees. ADT, a professional home security company, charges upwards of $600 annually for their most popular home security package in addition to installation fees which can run as high as $1,600 [2]. Though a smartphone-based home security system would not be a smart investment to purchase all at once, the retired phones mentioned earlier can be used as a home security system without purchasing any new hardware. Since most users are already familiar with the hardware and software of smartphone, it would be easy for them to set up and use a smartphone-based home security system in their homes. While several smartphone-based home security solutions exist, most of them use the device's camera to monitor events within the camera's field of view. These solutions have considerable drawbacks such as poor lowlight performance, using large amounts (several gigabytes) of storage, and the inability to detect break-in related events out of its field of view. Different from existing work, we study the feasibility of building a home security system based on smartphone accelerometers, magnetometers and microphones. Specifically, we will detect door and window opening events using the device's accelerometer, magnetometer, and microphone [23].

When a door is opened or closed, some of the kinetic energy transfers into the walls surrounding the door. The iPhone 4's accelerometer, with a maximum sensitivity of 1 mg/digit [3], has been proved to be capable of detecting keystrokes on a keyboard with an accuracy as high as 80% [4][24][25]. With this level of sensitivity, the six-year-old iPhone 4 is more than sensitive enough to detect vibrations in a wall caused by door activity. Newer phone models usually have as good or better sensitivity. Figure 1 shows our observation of vibrations caused by a door opening captured by accelerometer. This initial data was obtained by simply opening a door while an iPhone 6 mounted to the wall nine inches from the door recorded vibrations. It can be seen that door events emit distinguishable vibrational patterns. Most noticeably, when the device is mounted near a door in portrait orientation, door-related vibrations captured by the on-board accelerometer are especially large along the z-axis. Figure 2 shows a graphical representation of how the three motion axes are related to the orientation of the device. In addition to the accelerometer, the magnetometer can also be used to monitor the rotation of a door and detect door openings. By mounting a smartphone *on* a door (e.g., near the hinge) and monitoring the change in magnetic fields passing through the device, door events can be easily detected. We reference Earth's Magnetic North to determine how far the door has rotated - essentially using the smartphone as a compass needle while the door is the compass body. This method is less likely to produce false detection of door openings under environmental noise, although it cannot detect other events such as window openings when mounted on the door.

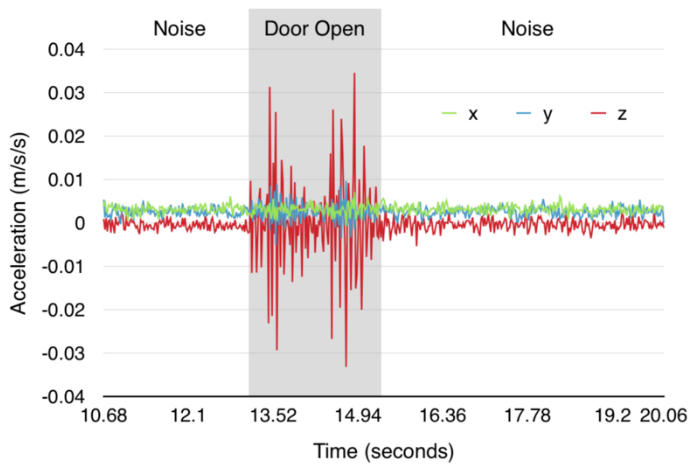


Fig. 1: Raw Vibration Data for Door Open Event

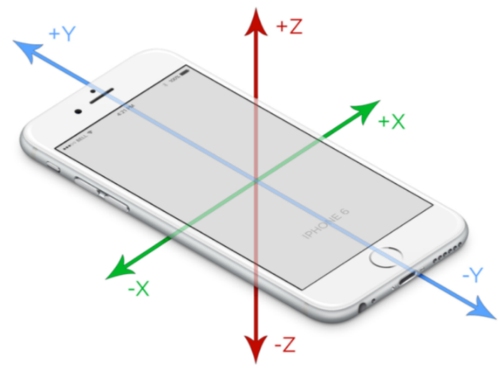


Fig. 2: Device Motion Axes

Though the accelerometer and magnetometer are very capable of detecting door open events, their effectiveness is closely tied to the phone's proximity to the door. With this in mind, we explore the possibility of using the phone's built-in microphone to detect the sounds of door openings. This approach allows us to place the phone in a more centralized location and monitor more than one door at a time. We use a neural network that specializes in categorizing images to classify spectrograms generated by the device. Figure 3 shows an example of one such spectrogram. Because each door has a relatively unique and distinct audio signature, we found it necessary to train the model on each door.

In this thesis, we explore several methods to use a smartphone's embedded accelerometer, magnetometer, and microphone to reliably detect door and window openings and propose a home security system (named *SecureHouse*) for break-in detection and notification

[23]. Upon event detection, the detecting smartphone can send a customizable notification to the homeowner via short message, email, and/or telephone call.

B. Contributions

The contribution of this thesis is summarized as follows:

1. We propose *SecureHouse*, a home security system based on smartphone sensors. To the best of our knowledge, this is the first study that detects door openings for home security purposes using the on-board accelerometer, magnetometer, and microphone of a smartphone.
2. We propose two machine learning methods to detect door openings using accelerometer data and one threshold-based method to detect door openings using magnetometer data. We also propose a machine learning method to detect door openings using sound.
3. We implement a prototype home security system. The system contains a mobile app which runs on a wall-mounted phone that can efficiently interpret sensor data and asynchronously dispatch notifications using its Wi-Fi connection, a 3D printed modular smartphone case specifically designed to capture vibrations in a wall, and a threat response server that sends out alerts to the homeowner in the form of text messages, emails, and phone calls.
4. We evaluate the system's effectiveness to detect door events using extensive experiments.

C. Organization of This Thesis

The remainder of this thesis is as follows. Chapter II presents related work. Chapter III presents the design of our system including system architecture and detection methods. Chapter

IV describes our prototype implementation. Chapter V describes our experimental methodology and evaluation results. Chapter VI concludes the paper.

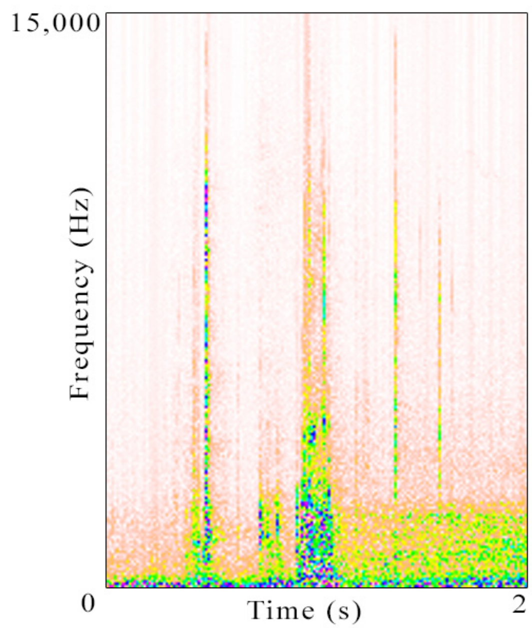


Fig. 3: Spectrogram Generated on Smartphone. Amplitude is represented by color and ranges from red to violet. To make the figure easier to read, we have replaced the red hues with white.

II. LITERATURE REVIEW

Wu et al. [5] propose a scheme to detect door events using the built-in barometer found in some modern smartphones. The key principle behind their work is that modern heating, ventilation and air condition (HVAC) systems maintain a constant pressure difference between inside and outside. Thus, when a door is opened, a sudden and recognizable change in barometric pressure occurs. We conducted experiments of our own using their methods and saw very similar results in a three-bedroom house. Specifically, we measured the fluctuation in pressure inside a home when a door is opened and closed. Figure 4 shows a clear change in pressure caused by door movement compared to background noise shown in Figure 5. However, the system can be rendered ineffective if the home has an open window since the air pressure inside and outside a home will be the same in that case. Figure 6 shows barometer readings from a door event when two windows are open. We no longer see the distinguishable curve similar to Figure 4, and the barometer readings become close to background noise shown in Figure 5. This is especially relevant where a homeowner might leave a window open while she is away (e.g., a window has metal bars on it and thus the homeowner considers it safe to leave the window open).

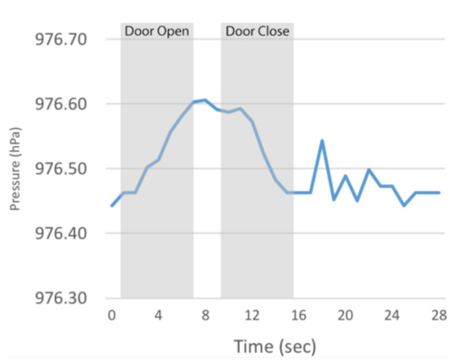


Fig. 4: Air Pressure Fluctuations for Door Event with Windows Closed

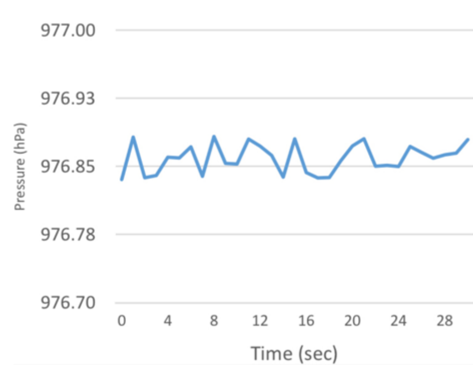


Fig. 5: Air Pressure Fluctuations without Any Door Events (noise)

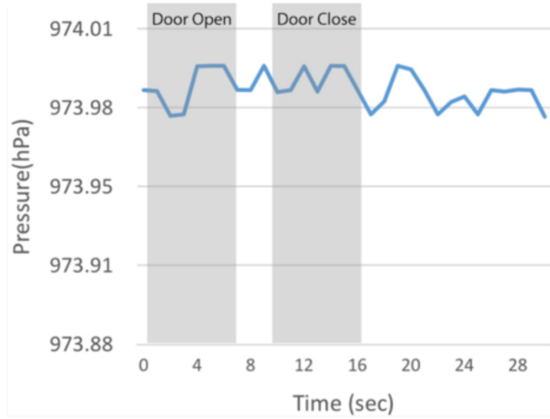


Fig. 6: Air Pressure Fluctuations for Door Event with Windows Open

Behringer et al. [6] have designed and implemented an automobile alert system using the accelerometer and GPS chips of smartphones. The system is capable of interpreting multiple types of car-related events such as engine ignition, door closing, and car motion. However, the system is designed for automobiles, not for home security.

Toyoda et al. [7] explore using neural networks to classify environmental sounds. Though this work is similar to a portion of our own, the team does not implement a security system based on the classification of sounds. Additionally, Toyoda's work does not limit itself to the processing power of a mobile device. Because of the extent of the limitations of using a smartphone to train and evaluate the neural network, we believe our work in that particular area is distinct enough to justify our work.

As to commercial products whose aim is to transform old smartphones into a security system, there are several published apps such as Presence, Manything, and Alfred [8][9][10]. These apps are among the most popular applications that use smartphones as a video-based home security system. These systems use simplistic video analyzation to detect motion within the camera's field of view under adequate lighting conditions. While they are effective for detecting general motion inside the home, their fundamental limitation is that a camera cannot detect motions out of its field of view and it requires good lighting conditions which likely are not available at night. Also, these systems can generate a large amount of data (more than 200GB [11] encoded as H.264 [12] at 1080p) each day which needs to be stored somewhere. Storing this data on the device itself is not practical because most mobile devices have between 16GB and 256GB of local storage. Naturally, these systems propose a solution by storing video on the cloud. In particular, Manything charges a Cloud Recording fee of $5.99 per month to be able to view past recorded events. This additional expense combined with the limited field of view and lighting requirements of a camera show that new technologies are needed.

III. SYSTEM DESIGN

A. System Overview

As shown in Figure 7, our system has three components: a wall-mounted smartphone, a response server, and the homeowner’s smartphone. The wall-mounted smartphone detects door opening events and dispatches a notification request to the response server. The response server sends out notifications to the homeowner via email, text message, and/or phone calls. Finally, the homeowner’s smartphone receives the notifications and alerts the homeowner.

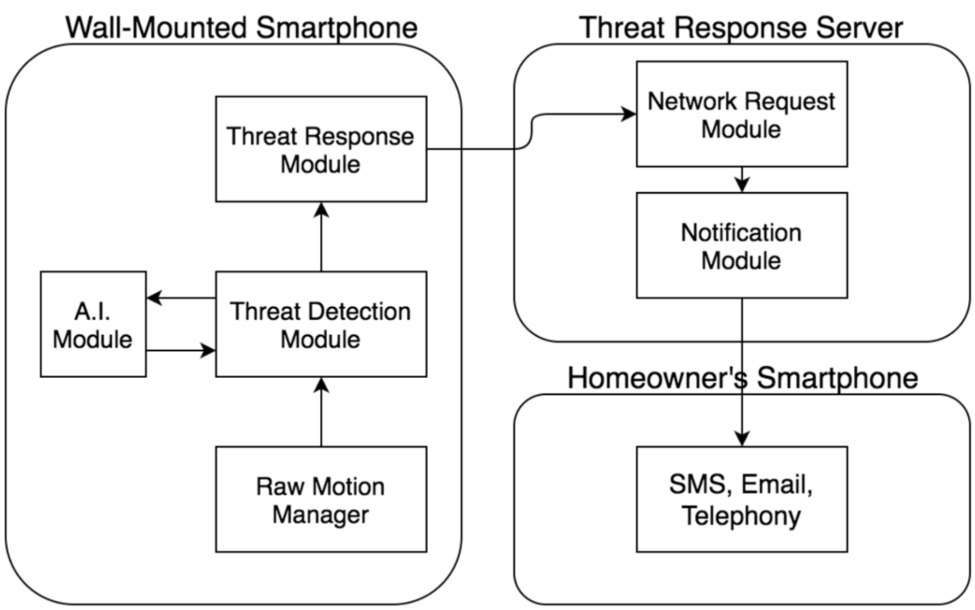


Fig.7: *SecureHouse* System Architecture

There are a total of six major software modules in our detection system; four in the wall-mounted device (included in one app) and two in the cloud-based threat response server. The homeowner’s smartphone does not require any other apps to be installed since the notifications arrive as text messages, phone calls, or emails which are already supported in nearly every smartphone.

For door opening detection, vibrational or magnetic field data is captured by the raw motion manager. This module is responsible for reading and interpreting raw acceleration and magnetic field data and audio samples. Thirty times per second, the manager pre-processes the motion sensor data and sends it to the threat detection module. This module implements a sliding window or acts as a data passer depending on the detection algorithm. For accelerometer-based detection via neural network and k-nearest neighbors (see Chapter III-B), the threat detection module asks the A.I. module for an interpretation based on the last 30 samples (1s) of data. For magnetometer-based detection (see Chapter III-C), the detection module simply performs the basic calculations and checks against a threshold to detect a door opening. Upon detection, the detection module notifies the threat response module, which decides the appropriate action to take based on certain conditions of the device such as whether the alarm function is turned on, internet connectivity, and user preference. When the alarm function is turned on and under normal circumstances, the threat response module will send an HTTP request to the Threat Response Server. The HTTP request will indicate what type of event happened and the homeowner’s preferred ways of notifications such as email, SMS, phone call, or a combination of them. In the case of Wi-Fi connectivity issues, the threat response module will play a loud alarm sound in an attempt to deter intruders. Under normal circumstances, the alert system will not play an alarm since this may panic the intruder- which could cause the intruder to become reckless, cause damage, and/or escape. The homeowner can disable the alarm when she is at home awake. She can turn on the alarm function before she goes to sleep or when she leaves home.

Our Threat Response Server is designed to run on any server capable of running Node.js programs. There are many such services available including free services. Our prototype system (see Chapter IV) is hosted by Heroku [13], a free third-party cloud application hosting platform. Several other free Node.js hosting solutions are available, such as IBM Bluemix [14], OpenShift [15], and Amazon Web Services (AWS). Incoming network requests (generated by the wall-mounted smartphone) are handled by the server's network request module. This module is simply responsible for handling and parsing incoming HTTP requests. After a network request has been processed, this module sends a message to the server's notification module, which will send out the alert according to the HTTP request. Though it is technically possible to use a home computer to perform this function, using an external server has a few important advantages. First, a user may want to change their notification preferences or silence the alarm while away from home. This can be easily done with an external server. However, for this to happen with a server at home, the homeowner would need to set up port forwarding on their router at home. This process is usually a little too technical for the average homeowner, and would be a detriment to the ease of installation of our system. Additionally, if any data related to a break-in is stored on the Threat Response Server, a burglar could potentially steal the server from the home and destroy some key pieces of evidence.

B. Accelerometer-Based Detection

1. A Naive Detection Algorithm

Before going to our proposed learning-based algorithms, we describe a naive detection algorithm. Being very simplistic in nature, the algorithm raises the alarm if and only if the vibration intensity (Vi) of each vibrational axis falls between a specific range α and β:

$\alpha_x < \mathrm{Vi}(x) < \beta_x$

$\alpha_y < \mathrm{Vi}(y) < \beta_y$

$\alpha_z < \mathrm{Vi}(z) < \beta_z$

This method does not use any sort of data queue or sliding window. It just checks every incoming value independently at 30Hz. The lower threshold α helps ensure that only significantly strong vibrations are considered - thus filtering out ambient and static noise. The upper threshold β helps filter stronger types of environmental noise such as the homeowner's footfall. In particular, since footfall and other vibrational noise affects all axes nearly equally while door openings affect primarily the z-axis, the upper thresholds β_x and β_y are substantially smaller in magnitude than β_z to filter such noise. This approach has several drawbacks. Since the thresholds are door-dependent and obtaining them takes several minutes of fine-tuning, it is nontrivial and annoying for the homeowner to find an effective set of lower and upper thresholds for each door upon installation. Moreover, it performs significantly worse than more advanced algorithms as to be shown later.

2. K-Nearest Neighbors + Dynamic Time Warping

K-nearest neighbors is a simple machine learning algorithm that classifies an unknown data point based on the classification of a certain number of "nearby" data points. For example, in 2-dimensional space, the distance between an unclassified point p and all other classified points is calculated. Then, we look at k points that are nearest to p and perform a majority vote. For our purposes, however, we are using a series of 90 points (thus, 90-dimensional space). These 90 data points represent any one-second window of vibrational data along three axes captured at 30Hz. To help keep our datasets consistent and to allow our models to be trained more effectively (especially for the neural network in III-B.3), our raw accelerometer data points are converted to a positive value (Vi) and then normalized from -1 to 1 (through dividing the value by the maximum recorded value, multiplying it by 2, and then subtracting 1). Lastly, we decouple the different axes from time such that the new curve takes the form of:

$$Vs = < x_1 \ldots x_{30}, y_1 \ldots y_{30}, z_1 \ldots z_{30} >$$

We call this new curve a vibrational signature. Figure 8 is an example of a common vibrational signature for a door open event. We can see from this figure that the z-axis (the last 30 samples) is most heavily affected by door open events, with almost no vibration detected in the y-axis (middle 30 samples). Since Euclidean and Manhattan distance do not work well for such high-dimensional datasets, we use dynamic time warping to measure how similar two vibration signatures are. Dynamic time warping is a common algorithm which excels in comparing the similarity between two time-series datasets. Specifically, it excels in determining similarities which span over different lengths of time. For us, this is especially useful for detecting different speeds of door openings. We set k equal to the square root of number of training samples. This choice has been shown by the literature to be effective and offers a more simplistic implementation than bootstrapping or cross validation. Since the training data needs to be generated by a human, the number of training curves is limited to 15-30 door events and 15 noise events (e.g., footfall inside the home and cars driving by). Due to the high dimensionality of the input, the number of training curves used, and the limited processing power of the phone, it is not possible to poll this algorithm at 30Hz. This problem is solved by waiting for significant vibrational disturbances using an activation threshold. In our experiments, we found that it is effective to set the threshold at 0.005 m/s^2. Disturbances greater than this threshold value trigger the analysis of a 1- second sliding window. The sliding window is essentially a queue that contains only the most recent 90 samples (one second at 30Hz for three axes) of accelerometer data.

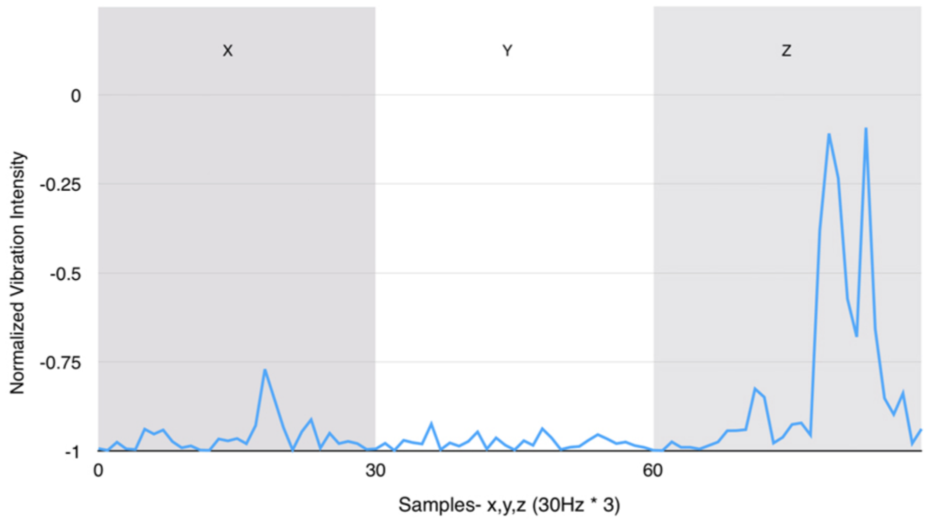


Fig. 8: Vibration Signature for Door Open Event

3. Feedforward Neural Network

In machine learning, artificial neural networks (ANNs) are known for the similarities they draw from biological brains. Instead of using neurons, an ANN uses sets of interconnected nodes. These nodes are separated into three main categories: input, hidden, and output. ANNs are generally known for their ability to generate nonlinear models based on high-dimensionality input data. Specifically, we use a feedforward neural network (FFNN). This means that data passes through the sets of nodes going in one direction only and there are no cycles allowed in the node graph. Figure 9 shows a graphical representation of what a generic feedforward neural network looks like at a high level. We choose to use an FFNN since its training phase happens all at once in the beginning of the program execution and because generating output from the model is very time-efficient. This benefit allows us to poll the FFNN at 30Hz on a resource limited smartphone.

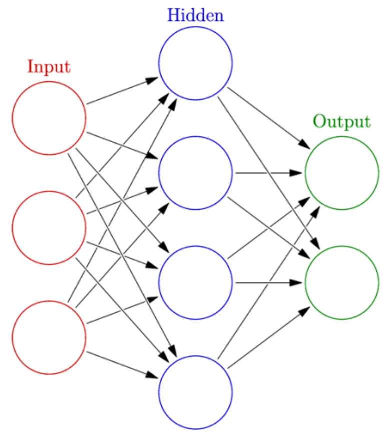


Fig.9: Representation of FFNN Nodes

For each door, a neural network is trained using 90-dimensional input data - exactly one second of 3-dimensional vibration data being captured at 30Hz. Due to the input requirements when training and evaluating the neural network, we use a *vibration signature* as defined above for our inputs instead of raw vibration data. We find that when using 90-dimensional data, using 60 hidden nodes ($90 * 2/3$) as suggested by Hundley [16] works well. We use one output node which simply returns a float value between 0 and 1. Values closer to 0 correspond to a lower chance of the interpreted data being a door event, while values closer to 1 correspond to a higher chance of a door event. Throughout this paper, we refer to this interpretation of the output value as the *assurance* of a door opening event. For example, if the *assurance* of the FFNN is set to 60%, we classify any output greater than or equal to 0.6 to be a door open event. Due to the prediction efficiency of this algorithm, we were able to use the same sliding window approach mentioned above to analyze a new vibrational signature every 0.03 seconds (30Hz).

C. Magnetometer-Based Detection

Figure 10 shows raw magnetometer data for a door open and close event. We see large, easily recognizable curves during the time the door is opening and closing. Very little jitter is seen in the magnetometer's readout, and practically no amount of vibrational interference would cause the readout to be significantly distorted. Though it may be possible for an attacker to use a strong magnet to interfere with the magnetometer, this would still alert the user because we do not use an upper threshold for event detection. Next, we look at a realistic threshold to trigger the detection. Since the data for a door event is easy to recognize, we simply use a threshold value to detect door events. We found that a difference of 2μT between the current value and the value when the door is closed worked well as a threshold to detect door events. Because Earth's magnetic field may differ from location to location, this approach will need to be calibrated/zeroed when installed in different locations. Different from the naive vibration-threshold method mentioned above, the homeowner does not need to fine-tune this system. He can simply hit an on-screen button while the door is closed to "zero" the magnetometer.

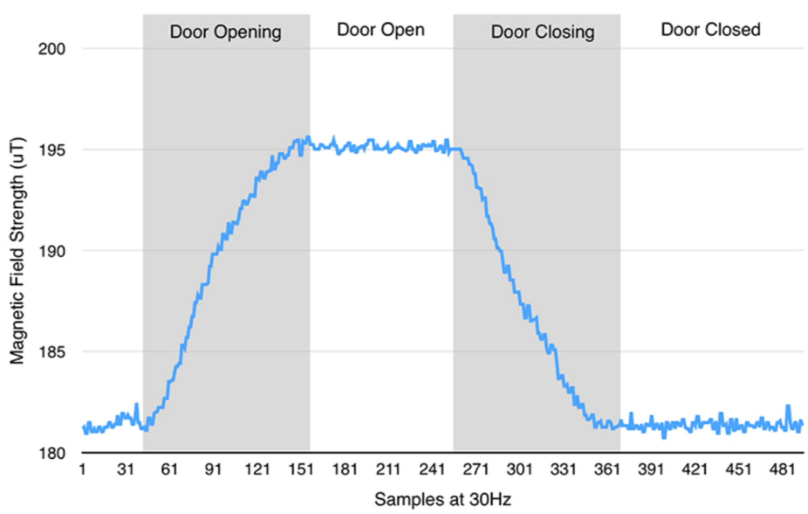


Fig.10: Magnetic Field Measurements of Door Event

D. Audio-Based Detection

In this section, we will present our audio-based detection method. For this, we created two implementations. The first implementation used raw audio samples, was very naïve and overall much less effective. Our second approach involved generating a spectrogram and using that for classification in a neural network. This approach worked significantly better, and we focus on this approach for our evaluation.

1. Using Raw Samples

A naïve approach to classifying sound is to feed the raw audio waveform directly into a neural network. Figure 11 shows an example of what raw audio samples look like when a door is opened. Though we can clearly see when the door is opened, there is a lot of jitter and oscillation in the signal. The main issue with this approach was that the lowest acceptable sample rate was around 8 KHz. This means when we analyze one second of audio, we have 8,000 samples to format and classify. Given the limited processing power of the smartphone and the relative inefficiency of Hundley's neural network library, this approach turned out to be too much for the phone's processor to handle. Nonetheless, we continued to lower the sample rate until the smartphone was able to process the signal in real-time. At 2 KHz, the phone was finally able to keep up with the influx of data, but the audio quality was so poor that the detection accuracy was reduced to less than 20%.

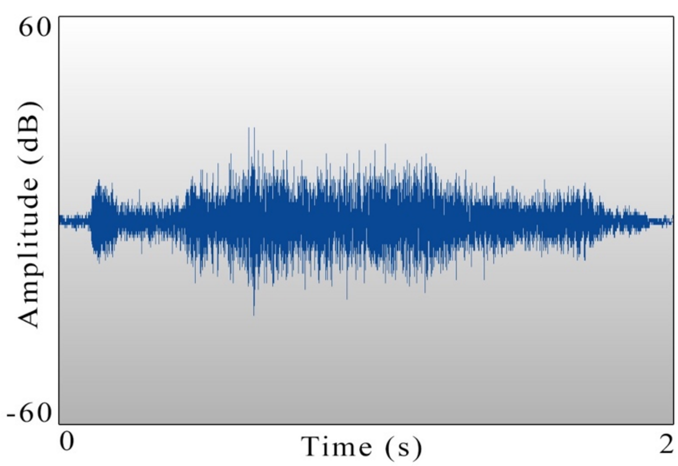


Fig.11: Raw Audio Samples of Door Open Event

2. Using a Spectrogram

In this approach, we convert the raw audio samples into a spectrogram using Apple's UIKit framework. Generally, spectrograms are used to represent the amplitudes of many frequencies over time [26][27][28]. Using a spectrogram, we can see a clear, distinguishable, and unique signal when the door is opened. To further increase the chance of success in this approach, we decided to abandon Hundley's neural network library in favor of Apple's recently released CoreML library [17]. This library is much more efficient, as it was specifically designed by Apple to take full advantage of the ARM architecture found in all Apple smartphones. This approach works by holding raw samples in a circular buffer and executing the spectrogram-generation and classification function on the buffer four times per second. In order to create a spectrogram, we first performed a Fast Fourier Transform (FFT) on the raw audio samples. From there, we normalize, filter, and crop the results to remove the mirrored data produced by the FFT. Finally, we can use Apple's UIKit to draw the spectrogram pixel by pixel. To visually represent amplitude, we simply mapped the amplitude to "hue" in the HSV color representation scheme, keeping saturation (S) and value (V) fixed at 100%.

Perhaps one of the most beneficial aspects of this detection method is its ability to self-train using the magnetometer as a ground truth. During the training phase, the phone is mounted on the door while the magnetometer provides a reliable way to distinguish noise events from door events. When SecureHouse is first deployed, the user only needs to mount the device on the door for a short time during which the neural network is trained. Afterwards, she is free to move the smartphone into a more central and less obtrusive location or continue training with more and/or different doors.

IV. IMPLEMENTATION

To demonstrate the effectiveness of our solution, we implemented *SecureHouse* as a prototype system. The following section describes some of the details and choices we made in the implementation phase.

A. Phone Software

Our detection system was written in Swift 2.3, compiled and tested using Xcode 7, and finally deployed on an iPhone 6 and 6S. We implemented our KNN+DTW algorithm from scratch, while our neural network was based on Collin Hundley's Swift AI library [16]. Because of the inefficacies of Swift AI, we were forced to use Apple's CoreML library when dealing with microphone data. In order to capture acceleration and magnetic field data programmatically, we used a low-level framework called Core Motion [18]. This library allows us to read the phone's acceleration and magnetic field data at a rate up to 100Hz. In order to conserve battery life and processing power, we chose to set 30Hz as the reading frequency. To capture sound, we used Apple's AVKit. This allowed us to capture and store individual audio frames from which we generated a spectrogram.

B. Smartphone Case

Additive manufacturing enables us to fabricate a smartphone mount specifically to suit our needs. Figure 12 shows a computer-generated model of the phone mount in its design phase and an image of the actual mount in use near a door. The case features a large back plate and screw holes so that it can be mounted on a wall near a door. The case's large flat back plate serves two purposes. The first being an easy way to attach the plate to the wall via the four screw holes. Second, and more importantly, because of its hardness and multiple contact points over a large surface area, it is able to mitigate vibrational dampening that may happen as vibrations transfer from the wall to the phone.

Fig.12: Smartphone Wall Mount

Though the mount is designed to be a permanent installation, the phone itself can be slid in and out of the mount with relative ease in the event of replacement, physical service, or reprogramming. We do not consider the ability to remove the phone from its mount a deficiency in its security system duties, as an attacker would need to already be inside the home to remove the phone from its mount.

C. Notifying the Homeowner

For simplicity and to allow a rapid development of this prototype system, our implementation of texting and calling uses Twilio [19], a third-party service that allows us to send texts and make phone calls by simply making an HTTP request. We also used an open source library called “nodemailer” that allows a Node.js server app to easily send emails. Figure 13 shows examples of alerts received by a homeowner in the form of a text message, an email, and a phone call.

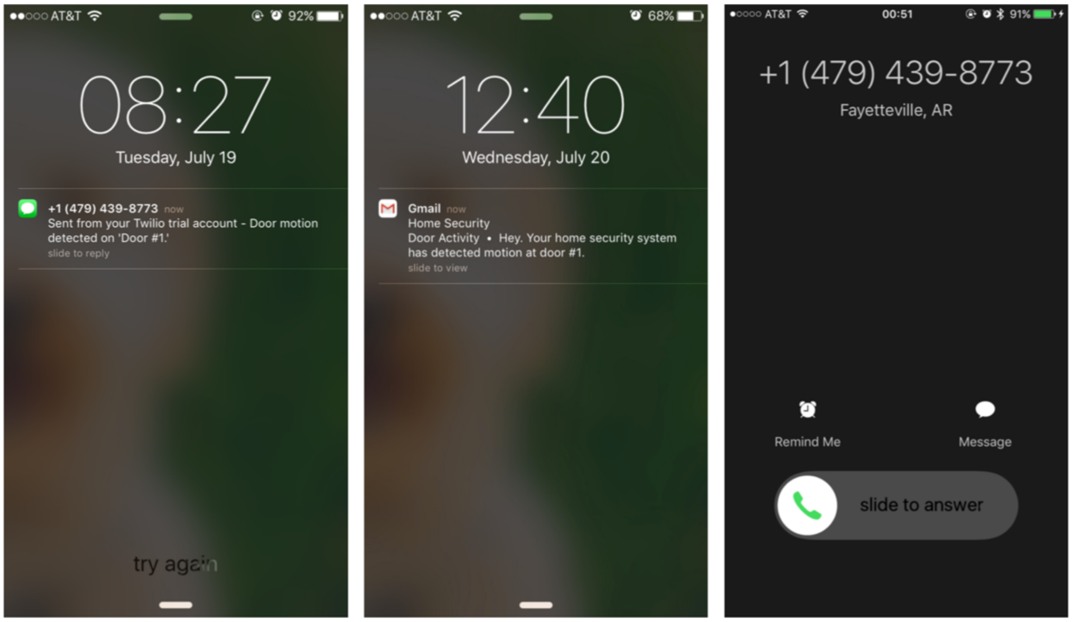


Fig.13: Example Notifications

Home automation is a growing market; many homeowners have automated lights, cameras, door locks, etc. Because of the rapidly growing nature of the industry, we provide a way to interface with many third-party systems that a user may have by providing user-configurable web-hooks. Web-hooks allow the user to specify a URL that an HTTP request should be made to upon door event detection. This allows SecureHouse to be easily and seamlessly integrated into many types of existing services. Possible integrations could include anything from turning on the homeowner's lights to playing loud music to deter intruders. If a service has a RESTful API, SecureHouse can interact and integrate with it. This functionality makes our system incredibly flexible and versatile, as there may be several unthought-of use-cases that could make SecureHouse even more effective.

V. EVALUATION

A. Experimental Methodology

The accelerometer-based experiments were conducted by mounting a smartphone on lightly textured drywall approximately 9 inches away from the latching mechanism of an exterior door. During the magnetometer experiment, the phone was mounted on the door itself near the hinge so that the phone would rotate when the door was opened or closed. For sound-based experiments, the phone was placed in a central location within direct line-of-sight of two exterior doors. The experiments were conducted in a 3-bedroom residential home approximately 20 feet away from the nearest road. Three types of vibrational noise scenarios were accounted for: ambient noise, walking noise, and automobile noise. Ambient noise was considered dead silence i.e. no external movement of any sort was present during the test. Automobile noise was generated by an automobile driving up and down the road closest to the house. Walking noise included normal to heavy footfall of people in the house during the trials. For acoustic noise, we considered loud footfall, talking, and automobile noise. Additionally, different speeds of door openings were accounted for. We considered three different types of door open speeds: slow, normal, and fast. We used a video camera and stopwatch to record and measure how long it took for a door to clear the door jamb at different opening speeds. Slow door events were classified as any door event in which the door took more than 0.6 seconds to clear door jamb. Normal events took between 0.3 and 0.6 seconds. Fast door open events consisted of any door events in which the door took less than 0.3 seconds to clear.

B. Detection Accuracy

Figures 14, 15, 16, 17, 18, and 19 show the detection rates for several series of door openings under various conditions using various detection methods. Detection rate is defined as the number of detected door openings divided by the total number of door openings. Here each result is the average of 50 independent tests. For the FFNN method, we ran tests with two different assurance values, one at 60% and one at 75%. For the microphone method, we trained the model organically for three weeks (i.e. the phone was mounted on the door for three weeks during the training phase). Figure 20 shows the overall detection rate for all tests.

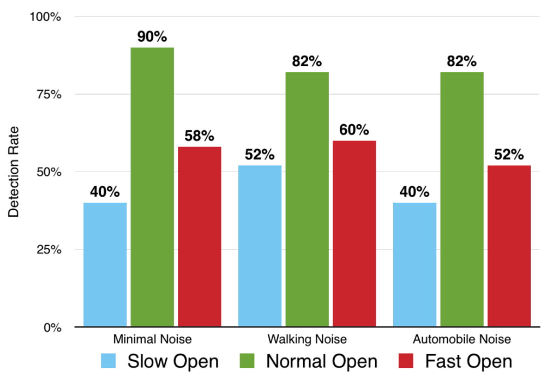


Fig.14: Vibration-based,
Naïve Method

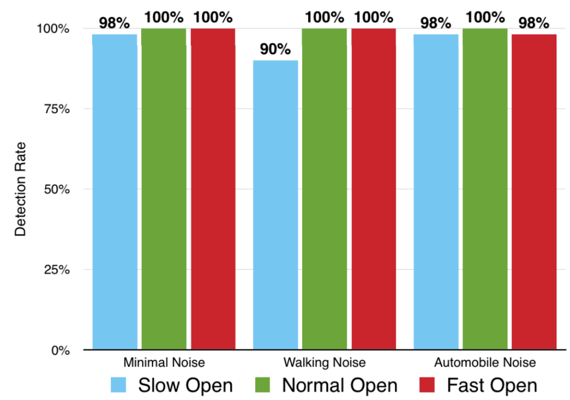


Fig.15: Vibration-based,
FFNN, 60% Assurance

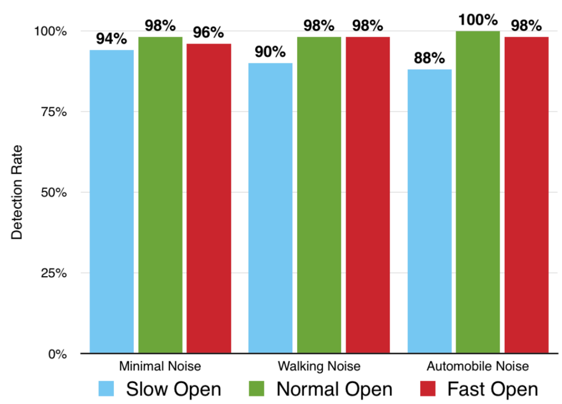


Fig.16: Vibration-based,
FFNN, 75% Assurance

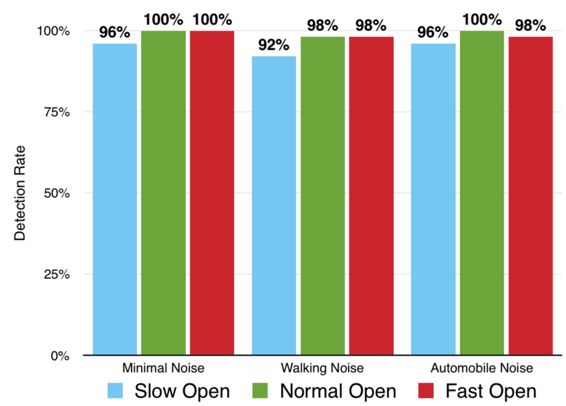


Fig.17: Vibration-based,
KNN + DTW

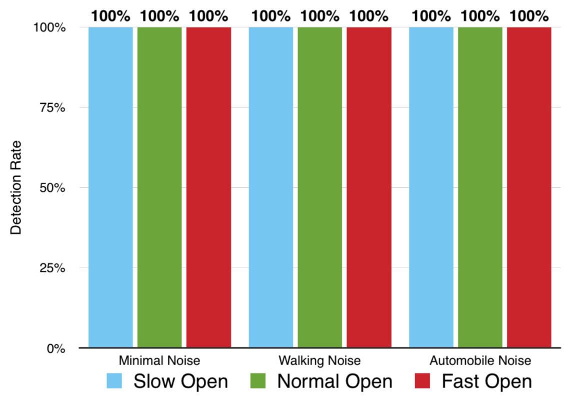


Fig.18: Magnetometer-based, 2uT Threshold

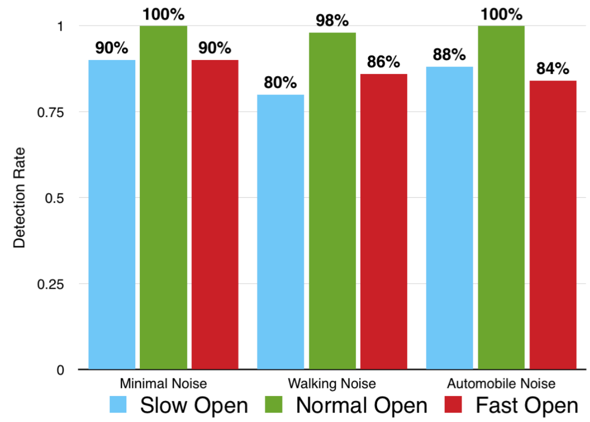


Fig.19: Spectrogram-based, 3-Week Training time.

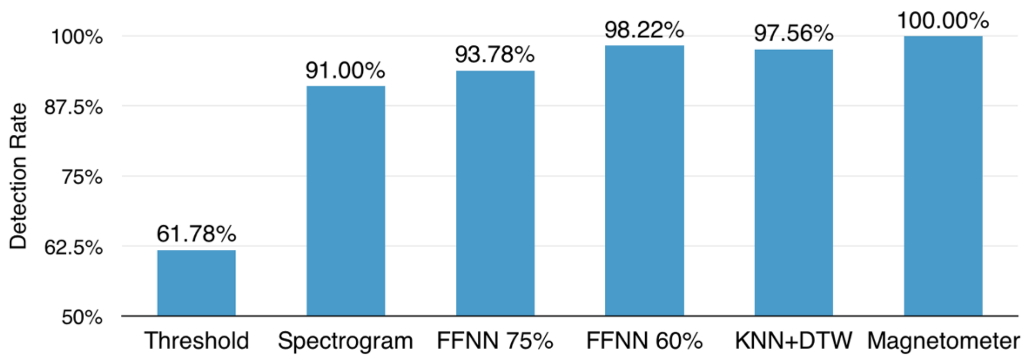
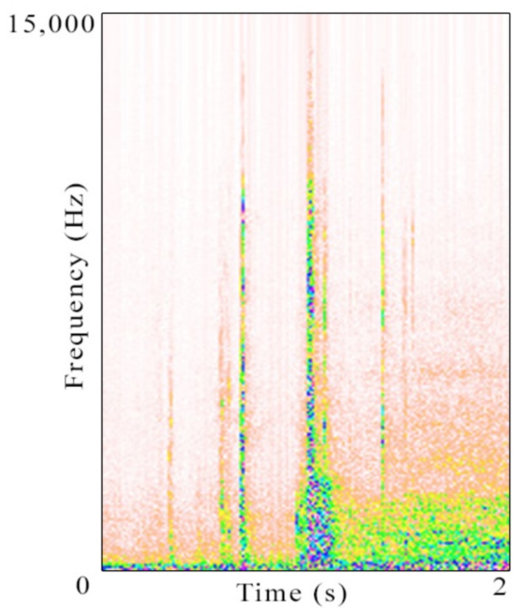


Fig. 20: Overall Detection Rate

Among the tested algorithms, the naive threshold-based detection using accelerometer data performs the worst, especially when the door is opened slowly. Its overall detection rate is 61%. The high failure rate of this system is due to our derived threshold values. Though a wider threshold would produce a higher detection rate, the increase in sensitivity would severely hinder its ability to filter false positives. The magnetometer-based detection performs the best with a detection rate of 100%, which is consistent with intuition since rotation of the door is significant when a person enters the house. The FFNN method (when assurance is set as 60%) and the KNN+DTW method also have a very high detection rate of 98%. The two machine learning methods perform similarly when the door is opened fast and when the door is opened at normal speed. The performance is a little lower when the door is slowly opened. For them, the different types of noise do not have much impact on detection rate when the door is normally or quickly opened, but have a little effect when the door is slowly opened.

For audio spectrogram-based detection, we see good performance under ideal circumstances. We notice that walking noise affects the detection accuracy more than automobile noise. This is expected, as walking produces more impulse-like sounds compared to the continuous "humming" sounds of nearby vehicles. Figure 21 shows an example of what a door opening looks like when a car drives by. We can see that automobile noise is mostly filtered until the door opens. Figure 22 shows an example of footfall in the home while a door opens. The sharp "spikes" are footsteps while the large colorful area in the center is the door opening.



. Fig. 21: Spectrogram of Door Opening While Car Passes

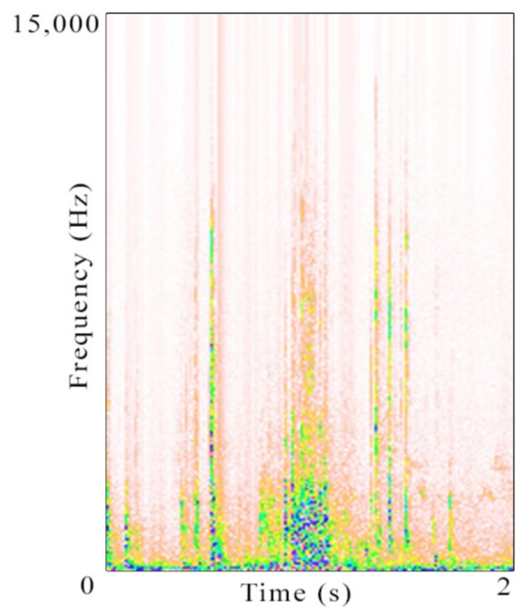


Fig. 22: Spectrogram of Door Opening with Footfall in Background

Table I shows the results of false detections caused by knocking on the door. For this test, we considered two intensities of a knock - light and heavy, and the number of knocks which occurred - 1 or 2+. It can be seen that the magnetometer has complete immunity to noise, while

KNN+DTW is only moderately affected by heavy door knocks. A single heavy door knock is the more likely to produce a false positive than other knocks.

TABLE I: False Positives Caused by Knocking on Door

	FFNN Light Knock	FFNN Heavy Knock	KNN+DTW Light Knock	KNN+DTW Heavy Knock	Magnetometer Light Knock	Magnetometer Heavy Knock	Spectrogram Light Knock	Spectrogram Heavy Knock
1 Knock	1/20	8/20	0/20	4/20	0/20	0/20	0/20	0/20
2+ Knocks	0/20	5/20	0/20	1/20	0/20	0/20	0/20	0/20

C. Field Tests

In addition to the 2,700 door openings performed above, we also let the system operate in a residential 3-bedroom home for short-term period 24 hours and a long-term period of 7 days. We conducted the 24-hour long test first to quickly determine which methods are most effective in a real-life scenario. We then used the top performing vibration-based detection method in our week-long experiment. We define false positives (FP) in these tests as any event that the device interprets as a door opening which was not a door opening. Table II shows the number of false positives during the 24-hour long test. Table III shows the results for the 7-day long test. We took note of whether a false positive was generated while no one was home versus while the home was occupied by the homeowner with the help of a video camera. Though we saw many false positives using vibrational-based detection under our machine learning-based detection methods, all of them occurred while the homeowner was awake at home. We found that our 3-bedroom house generated a large amount of highly varied environmental noise such as playing aggressively with dogs, loudly stomping about, and large groups of excited people during televised sporting events. Since the alarm function can be disabled during these times, those false positives will not cause false warnings to be dispatched to the homeowner.

TABLE II: Field Tests over 24 Hours

Detection Algorithm	**FP- Homeowner is Away**	**FP- Homeowner is Home**	**False Alerts- Home- owner is Away**	**False Alerts- Home- owner is Home**
Vibrations-Threshold	2	22	2	0
Vibratoins-FFNN-75% Assurance	0	9	0	0
Vibratoins-FFNN-60% Assurance	0	21	0	0
Vibrations-KNN+DTW	0	19	0	0
Magnetometer 2μT	0	0	0	0
Audio Spectrogram	0	18	0	0

TABLE III: Field Tests over 7 Days

Detection Algorithm	**FP- Homeowner is Away**	**FP- Homeowner is Home**	**Unnecessary Warnings**
Vibrations- FFNN 75% Assurance	0	53	0

D. Modeling Vibration Dissipation

In order to determine the generality of vibration-based detection, we want to estimate a maximum distance away from a door that a smartphone could be mounted and still be effective. Specifically, we are interested in finding a distance such that $Vi_{\text{door open}}(x, y, z) \leq Vi_{\text{noise}}(x, y, z)$. After this distance, the vibration caused by door open is too small to be differentiated from background noise.

To answer this question, we need to figure out how fast vibration dissipates in the wall. It is generally known in physics that the rate of energy dissipation from a single point in space can be modeled by: $f(k) = \alpha e^{-\lambda x}$ [20]. Our goal is to determine a suitable value for λ and α such that we may generalize how fast vibrations dissipate through the walls in a home. To do this, we purchased several high-sensitivity accelerometers [21] and mounted them at 1 foot intervals on a wall next to an exterior door. Figure 24 is a picture of the experimental setup. To generate a consistent source of vibration, we attached a rubber ball to a string of fixed length, and used it as a pendulum to strike the wall. Figure 23 shows the average result of 10 tests and a best-fit line from which we get the α and λ. Using this dampening rate (determined by λ) and our measurement of vibration strength near the door for door open, we can generate a theoretical vibration curve for several distances away from the door. We found that after distances become greater than 6ft, the magnitude of door-related vibration was less than or equal to that of ambient noise. We acknowledge that the dissipation rate might be different for different walls, but the result here can still shed some light on the effective distance of vibration-based detection.

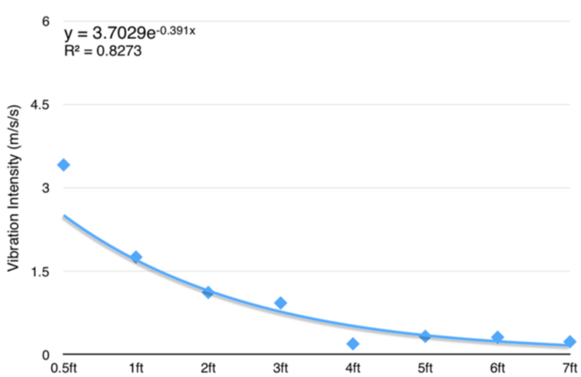


Fig. 23: Model of Vibration Dissipation in Drywall

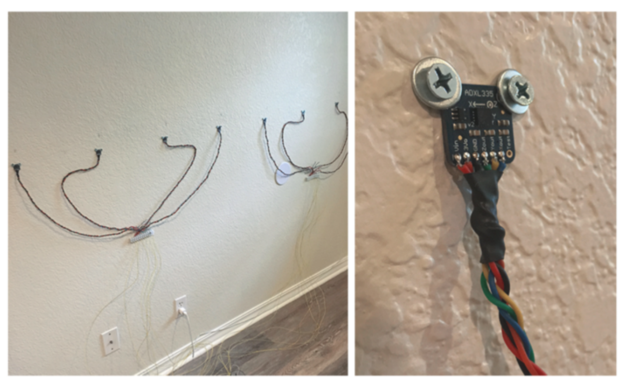


Fig. 24: Experimental Setup for Modeling Vibration Dissipation

E. Door Proximity & Interference

In modern living spaces such as apartments and duplexes, exterior doors might be placed in close proximity to each other. We set out to determine if doors in close proximity would have any noticeable effect on our detection methods. We started out by visiting a local apartment building and taking some measurements. We measured 24’ 9” as the horizontal distance between doors, and 7’ 6” as the vertical distance between doors. With the smartphone mounted on the wall near a door, we opened and closed next-door neighbors’ doors several times and recorded the vibration intensity. We did this experiment for neighbor doors on the same floor, and the floors above and below. We observed that neighbors’ doors had virtually no impact on the vibration readings. This was expected, though, as our dampening model had predicted distances greater than six feet would be enough to reduce the magnitude of vibrations to that of environmental noise.

F. Detecting Other Motion Events

Although the detection rate of vibration-based and audio-based detection is a little lower than the magnetometer-based detection, they have one distinct advantage: they can detect other motion events in addition to door open. To demonstrate this, we conducted tests for window openings. For the accelerometer test, the window is 42 inches away from the wall-mounted smartphone. For the microphone test, the window is about eight feet away and in direct line-of-sight. For these tests, we trained the two types of neural networks using 15 samples of window openings and 15 samples of noise (8 samples of ambient noise, and 7 samples of heavy footfall). The assurance parameter was set to 60% and the same 1-second sliding window described above was used. This implementation was nearly identical to how we detected door open events using the neural networks. We tested 25 window openings. The detection results are shown in Table IV. 92% of the window openings can be detected.

TABLE IV: Window Opening Detection

Detection Algorithm	Detection Rate
FFNN – 60% Assurance	23/25
Audio Spectrogram	20/25

We see that the microphone-based method performs a little worse than the accelerometer-based method. Though the results are slightly less accurate, the microphone is capable of detecting window openings for multiple windows whereas the accelerometer is limited to just doors and windows within six feet of the phone.

G. Cost Evaluation

In this section, we will describe how we evaluated the cost of our system as well as the results compared to a few other popular smartphone applications.

1. Processing Time

For feedforward neural network, the algorithm is able to analyze a curve in 0.0011 seconds. Since we are polling this algorithm at 30Hz (0.033 seconds), our program spends only 3% of its runtime analyzing curves, and the remaining 97% is spent idle. The KNN+DTW approach needs a much higher processing time. Each analyzation takes 0.76 seconds. This is because the DTW algorithm has high time-complexity ($O(n^2)$), the method does not have a training phase, and it uses 30 curves.

2. Memory Usage

The total size of our packaged detection app is around 20MB. This is on par with or lower than many apps in the App Store. Our app does not write any data to disk during operation, so we can expect this value to remain constant during the life of the operation. For memory consumption, our analysis shows that the FFNN detection algorithm uses 5.8MB of memory on average, while the KNN+DTW detection algorithm uses 5.5MB on average. Our sliding window contains 90 doubles, which iOS allocates 8 bytes [22] each to. Our sliding window releases unused values, so we say the extra cost of the sliding window is less than 1KB.

3. Network Usage

The SecureHouse detection app only uses the network when a door event is detected. Upon door event detection, a POST request is made to the threat response server which contains only an 128-bit access token and two integers representing the type of event and the homeowner's notification preferences. The total size of this request is less than 350 bytes. This results in around 15KB of data being sent per day when the home is in use, and near 0KB of data being sent when the homeowner is away.

4. Power Consumption

iOS does not support gathering of energy consumption in units of mW, so we used Xcode's Instrument Panel to monitor energy consumption. This tool allows us to see an "energy usage level" on a scale of 0-20. For the FFNN, KNN+DTW, and Magnetometer detection methods, our app achieves a rating of 0 (best) for energy consumption. Furthermore, the energy-consumption tool shows that the detection methods use between 6% and 15% of the CPU cycles. We found that this is much lower than other types of apps. In particular, Crossy Road, a popular mobile game scores a 3/20 and uses between 39% and 58% of the CPU cycles.

While Chrome, a web browser for iOS, scores a little better with a rating of 0/20 but uses an average of 21% of the CPU cycles. In order to get a better feel for the power consumption of our detection app, we ran experiments and found that it takes more than 80 minutes to deplete an iPhone 6's battery by 10% while running any of the detection algorithms. This means that, though the phone would need a permanent power source, the system could remain operational for more than 13 hours in the event of a power loss.

VI. CONCLUSION & FUTURE WORK

This paper studied the feasibility of using the accelerometer, magnetometer, and microphone of a smartphone to detect door openings and build a home security system. We developed two machine learning based detection methods using the accelerometer data, one detection method using magnetometer data, one detection method using the microphone, and developed a prototype system. Experiments showed that door openings can be accurately detected using accelerometer and magnetometer data, with a detection rate of 98% and higher. The microphone can detect door openings across multiple doors with an accuracy of 90%. Accelerometer and sound-based detection can also detect window openings with high accuracy. Smartphones containing built-in Wi-Fi connectivity are easily capable of dispatching alerts to the homeowner or even law enforcement. Thus, our smartphone-based home security system built with retired smartphones could be a viable and economical option for residential homes.

As for future work, our system could be expanded upon in several ways. First, as it stands currently, if a user wishes to use the accelerometer, she must manually train the model by opening the door several times for each door. Compared to the magnetometer and microphone-based approaches, this is a bit clunky. Perhaps we could gather enough data on many doors to create a generalized prediction model so that a potential user can skip this training process. Though the microphone-based detection method uses the magnetometer to train itself, three weeks is quite a long time for the device to spend in training mode. Again, we could potentially create a generalized model for this such that it can classify most door openings without extra training from the user. Second, since vibrations caused by door opening dissipate quickly and become indistinguishable from environmental noise after 6 feet, most likely a smartphone mounted near one exterior door can only detect the openings of this door when relying on vibrational data. There are many apartments and small duplexes that only have one exterior door or doors near each other. For a large house with multiple exterior doors, using one smartphone for each door, although not totally infeasible (e.g., when there are multiple residents with multiple retired phones), seems too costly. In this scenario, we recommend using the audio-based detection method, as it can detect several doors while in a central location. In our future work, we will investigate a way to improve the audio-based detection method.

Finally, we could further augment SecureHosue to incorporate even more sensors and detection methods. This could include the use of more passive detection methods like Bluetooth and Wi-Fi scanning or even using the barometer in conjunction with the other detection methods. Ideally, we want to create a system which can use a single device to detect, report, and deter break-ins regardless of any environmental variables.

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