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A SECURE HOUSE BASED ON SMARTPHONE SENSORS WITH IOT

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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 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.

Keywords: Smartphone, IOT**,** sensors, MEMS**.**

1. INTRODUCTION

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.

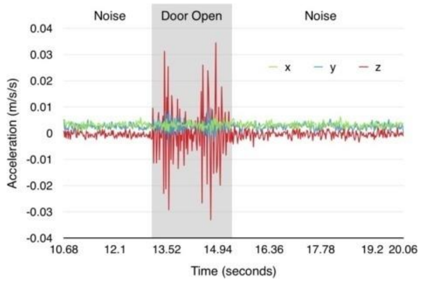


Fig. 1: Raw Vibration Data for Door Open Event

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 onboard accelerometer are especially large along the z-axis.

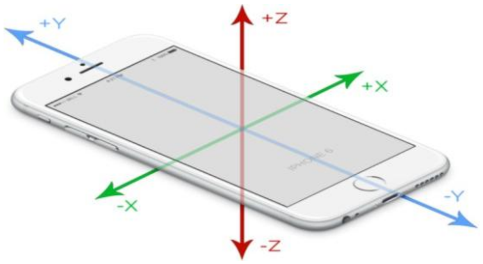


Fig. 2: Device Motion Axes

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 3 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. 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 Secure House) for break-in detection and notification.

2. BACKGROUND SURVEY

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.

3. METHODOLOGY

- ✦ We propose Secure House, 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.
- ✦ 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.
- ✦ 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.

- We evaluate the system's effectiveness to detect door events using extensive experiments.

4. SYSTEM IMPLEMENTATION

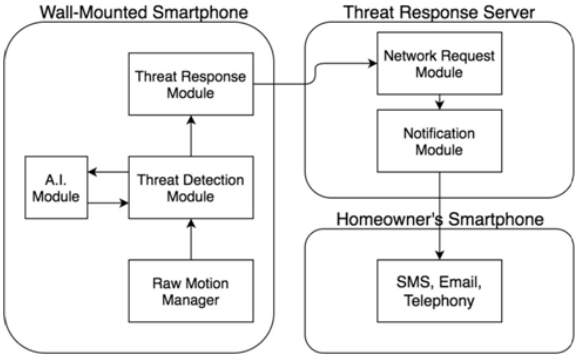


Fig.10: Secure House System Architecture

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.

There are a total of six major software modules in our detection system; four in the wallmounted 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, 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, 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.

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.

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.

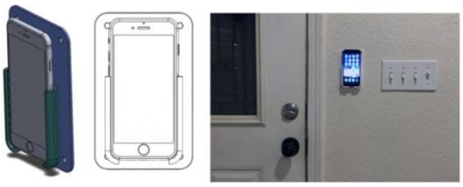


Fig.16: Smartphone Wall Mount

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 "node mailer" 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.

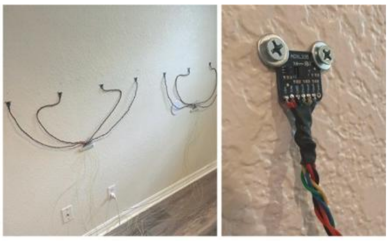
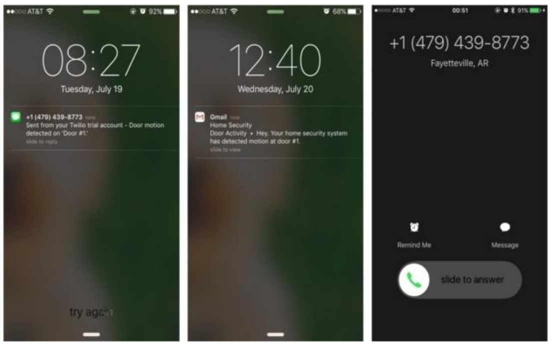


Fig. 36: Experimental Setup for Modeling Vibration Dissipation

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 Secure House 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, Secure House 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 Secure House even more effective.



08:27
Tuesday, July 19
+1 (479) 439-8773 now
Sent from your Twilio trial account - Door motion detected on 'Door #1.'
slide to reply

12:40
Wednesday, July 20
Gmail now
Home Security
Door Activity • Hey. Your home security system has detected motion at door #1.
slide to view

+1 (479) 439-8773
Fayetteville, AR

Fig.17: Example Notifications

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.

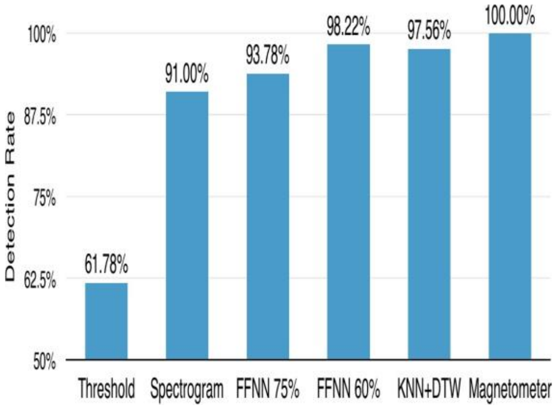


Fig. 32: Overall Detection Rate

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.

5. CONCLUSION

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 microphonebased 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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