DeepScanner: A Deep Learning-based Stud Finder Exploiting Real-Time Sound In A Smartphone

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Thesis directed by Prof. Sangtae Ha

Recent advances in mobile devices, having embedded sensors and high-performance processors, enable the users to collect sensor data and utilize them more easily. These improvements in accessibility have led to beneficial developments in many areas. In this paper, we present Deep-Scanner, which finds a stud only by knocking with a smartphone. Deep-Scanner utilizes a microphone and accelerometer sensor to collect knocking sounds and exploit 1D-Convolution Neural Network to identify a stud. In our experiment, our model achieved high accuracy up to 97% with samples of 4-inch intervals. It also can find the stud with an accuracy of less than 0.75-inches.

Dedication

This work is dedicated to my family and parents for all their supports and encouragement, especially for my wife Kiyoung and newborn baby Jiwoo.

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Chapter 1

INTRODUCTION

Finding a stud behind the wall is a frequent problem in our daily lives. When hanging heavy objects on the wall such as shelves and television or extending the wall to divide a room, we should find studs to ensure enough support. If we do not screw or nail into the wall stud firmly, the weight can pull out the wall's fasteners and cause an accident. There have been numerous approaches to find the stud, and these devices are known as 'stud finders.' Those stud finders can be categorized into three types by their stud finding methods: magnetic, electronic, radar stud-finders. The magnetic stud finder is the first generation of stud-finders, and it is still in use due to its simplicity. It uses a stationary magnet to detect the metals in the drywall, like nails or screws placed on the stud—most smartphone stud finder applications also find the stud utilizing magnetometers. The magnetic stud-finder problem is that other materials such as water pipes, electric wires, etc., contain enough metal to confuse the stud finder. The electronic stud-finder is the second generation of stud-finders. It relies on sensors that detect changes in the dielectric constant of the wall. The density difference on the wall brings capacitance change, and when the difference exceeds a certain threshold, the device regards it as the existence of a stud. The electronic stud finder is the most widely used today, but the electronic stud finder's drawback is that it is hard to find its edge accurately. This difficulty occurs because every wall has a different permittivity value, but the stud finder has a determined threshold. Therefore, the user has to find the points where the stud finder indicates when it is scanned from the left and right sides and find the middle of those points to ensure nailing on the exact stud. Recent electronic stud finders solve this problem by installing more sensors and calculating the difference between them [16]. This approach gives higher accuracy but costs more than the basic stud finder. The most advanced approach to stud finder is utilizing radar for scanning [8]. They detect the materials by transmitting high-frequency radios (e.g., mm-Wave) and acquire information about the materials. This method shows the highest accuracy of finding stud and can distinguish the types of material behind the wall. However, this kind of stud finder requires the users to buy a specially designed module that contains radar sensors, and they are usually costly.

Modern smartphones embed a rich set of sensors such as GPS, camera, accelerometer, gyroscope, and magnetometer. They also allow users to access those sensor data. This paper proposes a new way to find a stud by classifying the impact response sound using a microphone and accelerometer sensor on a smartphone. As described in the figure 1.1, a user holding a smartphone perpendicular to the wall knocks on the wall to find a stud. By recording and analyzing the response sound, the user can detect a stud's existence. We implemented DeepScanner on a Google Pixel XL and evaluated its performance. Our evaluation shows that DeepScanner can find a stud under 0.75-inches accuracy in residential buildings even in a noisy environment. DeepScanner solves two challenging issues: (1) how to pinpoint the exact location of the stud by distinguishing knocking sounds from ambient sounds; and (2) how to accurately distinguish between knocking sounds as the Deep Scanner gets closer to the stud.

This paper makes the following contributions:

(1) We introduce DeepScanner. Unlike existing stud-finder applications that use Magnetometers, DeepScanner exploits a new way to find studs using impact response sound with smartphone sensors without any specialized hardware.

(2) We present DeepScanner's deep neural networks to automatically find features from the frequency spectrum and classify the input sound automatically.

(3) We implement DeepScanner on commodity smartphones and empirically show the efficacy of DeepScanner.

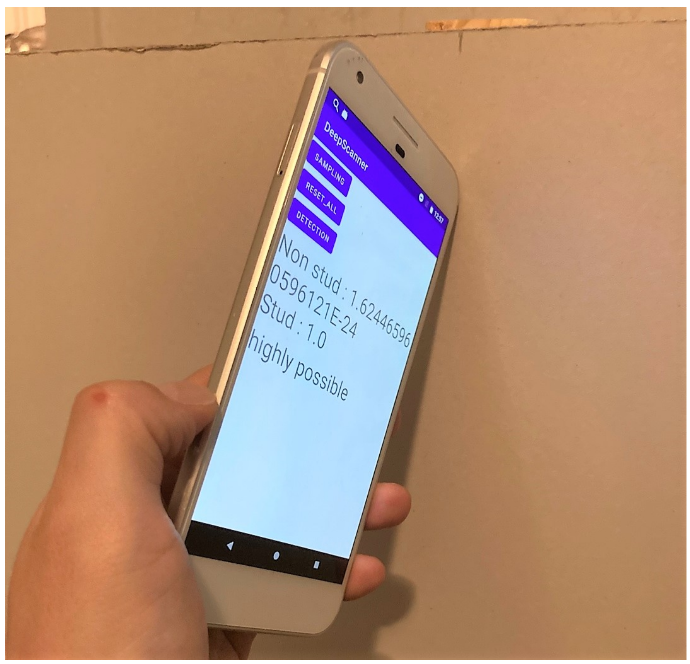


Figure 1.1: DeepScanner demonstration.

Chapter 2

BACKGROUND

This section describes constructing residential walls in the U.S (United States) under IRC (International Residential Code) regulation codes and explains the materials' Natural Frequency.

2.1 Wall construction

The stud wall is a standard residential wall built with studs and wallboard. After making the frame with studs, the wallboard is attached and finished. There are various materials and types of studs and wallboards, but the most dominant construction materials are a wooden stud and drywall known as sheet-rock or gypsum board. According to the gypsum association, the drywall covers the interiors of 97 percent of new homes constructed in the U.S and Canada since the early 20th-century [3]. Also, the U.S Department of Housing reports that wooden studs make up 98 percent of all interior walls in 1990 [14]. Since the stability verified and having price competitiveness due to mass production, wooden studs and drywall still take the dominant materials in the construction area. For these reasons, we performed all tests on the walls built with wooden studs and drywall-board in this paper.

The IRC is the main code for residential construction in North America. They establish the minimum safety regulations for family housing:

- `Stud space`: The maximum wall stud space with drywall is 16 inches.
- `Wood grade`: The wood for the stud should have No.3 grade at least.

Figure 2.1: Wall frame construction example.

To minimize construction costs, most construction companies comply with minimum standards of the regulation. Therefore, in our research, we also used the IRC minimum standards as the default setting value.

2.2 Natural frequency

Each material has its elasticity and frequency of vibration, which is called natural frequency. When the material receives an external impact force, the natural-frequency oscillation of the material makes continuous pressure on the air, and this pressure propagates throughout the surrounding area. This mechanism shows how external impact creates a sound and why it resonates with the material's natural frequency. Utilizing this feature, we can detect the differences of material from the change of frequency. There have been many experiments and tests, especially in the construction area. Calculating the natural frequency is essential in the construction area because it has a close relation to the building's resonance frequency which can cause the collapse of the building. The natural frequencies for the vibration of materials can be calculated using the following equation 2.1 [15]:

$$f = \frac{A}{2\pi}\sqrt{\frac{EI}{\mu L^4}} \tag{2.1}$$

$$I = \frac{wt^3}{12} \tag{2.2}$$

Where:

E = Modulus of elasticity

L = Free length of material

w = Width

t = Thickness

I = Area Moment of Inertia

μ = Mass per unit length

A = Coefficient

Chapter 3

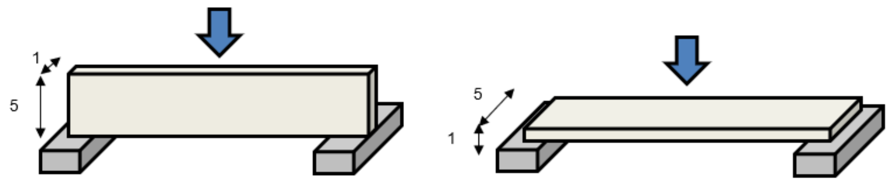
FREQUENCY DIFFERENCE

We presumed that there would be a frequency difference between wooden studs and a gypsum board. There could be some difference in the variables of the natural frequency equation depending on the type of wood and gypsum board. Still, they are not different in their material, resulting in similar elasticity and density, as specified in Table 3.1. When it comes to the mass per unit length, even though the width of a gypsum board is ten times broader than the stud's width, the stud is also seven times thicker than the gypsum board. Therefore, as width and thickness offset each other, there is little difference exist by length. The fundamental difference exists in the area moment of inertia. The area moment of inertia is the deformation resistance, which is also known as the second moment of area. As the area moment of inertia increases, the material deforms less. For this reason, the wavelength of the sound becomes shorter and makes a high-frequency sound. Since the inertia increases in proportion to the thickness's cube, the stud has more inertia than the gypsum board. Figure 3.1 shows an example of a significant difference in area moment of inertia by thickness.

Table 3.1: Material properties.

Material	Elasticity	Density
Gypsum board(1/2inch)	4350MPa[13]	700 kg$^3/m^3$[4]
wooden Stud(Stud grade)	4000MPa[7]	700 kg$^3/m^3$[17]

We construct a wall model in the same size as actual wall construction and tested the knock



$$I = \frac{1 \cdot 5^3}{12} = 10.416 \qquad I = \frac{5 \cdot 1^3}{12} = 0.416$$

Figure 3.1: Example of an area moment of inertia difference by thickness.

sound frequency with studs (Figure 3.2).

Presence of horizontal blocks between studs. A block is a horizontal strut that is positioned between the studs and provides lateral support to them. Since blocks can affect the frequency distribution of impact sound, we installed blocks in the model and compared the frequency distribution changes with and without blocks. As shown in Figure 3.3, we couldn't find a significant difference in frequency distribution between with and without blocks. We found that the bonding between drywall and studs make a difference. Unlike the studs firmly bonded with screws, blocks are not strongly bonded with the drywall. Therefore, a fine gap exists between the blocks and drywall, preventing the impact energy of knocks from being transferred.

We collected and compared measurement samples from nine points around the stud, as shown in Figure 3.4. Using Fourier transformation, we could get the frequency domain result from the raw sound data. Figure 3.5 shows the results that correspond to nine points in Figure 3.4. We can see that three measured points in the center (L2, L5, and L8), where a stud exists, show the presence of higher frequency signals.

Figure 3.2: Wall model.

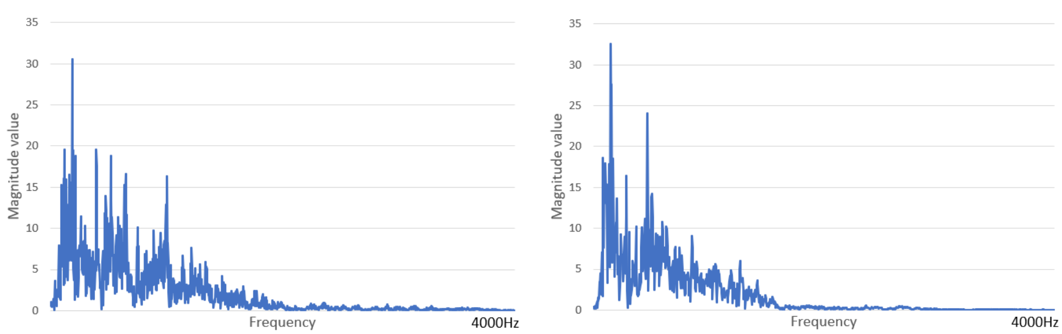


Figure 3.3: Frequency distribution on the presence of blocks. (left: without blocks, right: with blocks)

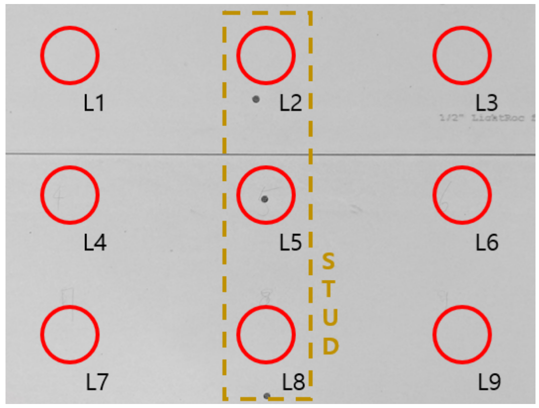


Figure 3.4: Sampling points of the wall model.

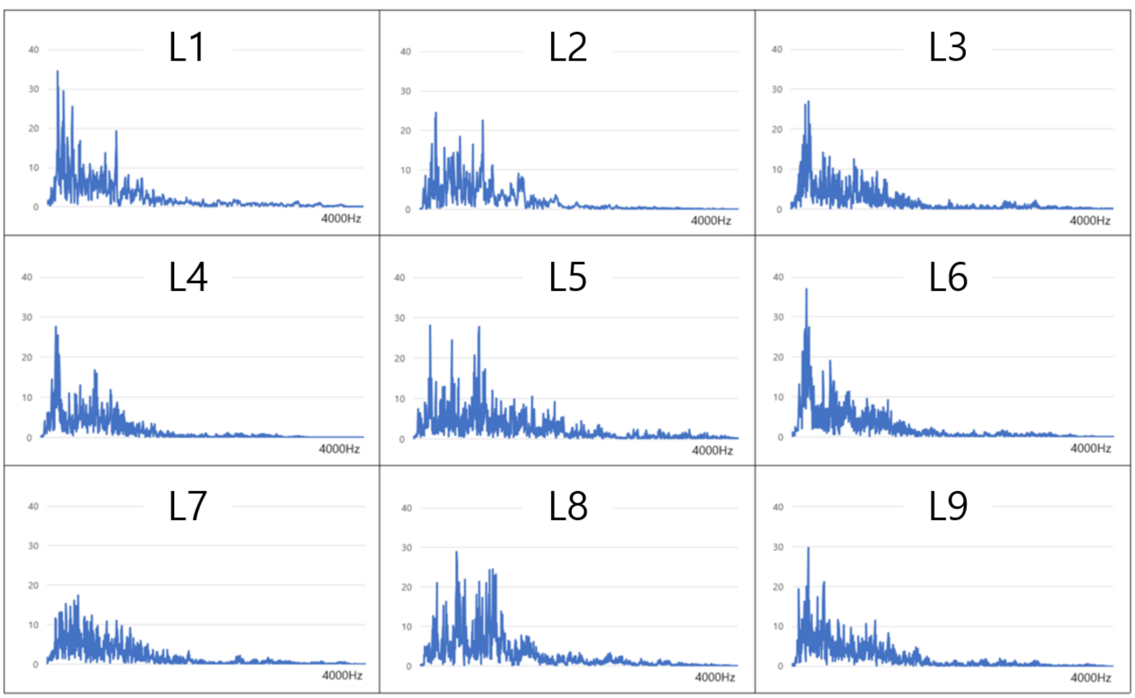


Figure 3.5: Frequency distribution of the sound extracted from Figure 3.4.

Chapter 4

DEEP SCANNER SYSTEM

We propose an impact sound sensing system, Deep-Scanner, which measures the impact-response frequency difference and determines the stud existence using microphones in the smartphone.

4.1 Design challenges

There are several challenges to find studs using the impact response sounds from the wall.

Capturing knocking sounds: A knocking sound is an impact-response sound that disappears in a short time. It is not straightforward to extract knocking sounds from the ambient sound. To acquire the knocking sound on time, we utilized the accelerometer sensor. When the user knocks on the wall, there is an abrupt value increase in the accelerometer value. Therefore, if the accelerometer exceeds the threshold, we considered it as a knock.

Identifying studs: Since the wallboard is firmly attached to the stud, the knocking sounds right over the stud are different from the sounds far away from the stud. However, the knocking sounds very close to the stud are not largely different, so finding the exact location of a stud is challenging. To mitigate this issue, we collect samples with a certain distance from the stud, so that machine learning (ML) techniques can catch a slight difference of knocking sounds near the stud as well. Furthermore, labeling measurement samples differently that do not have much of a sonic difference confuses classification. Our experiment collected the knocking sound samples between two studs (16 inches apart) with 4 inches of intervals horizontally.

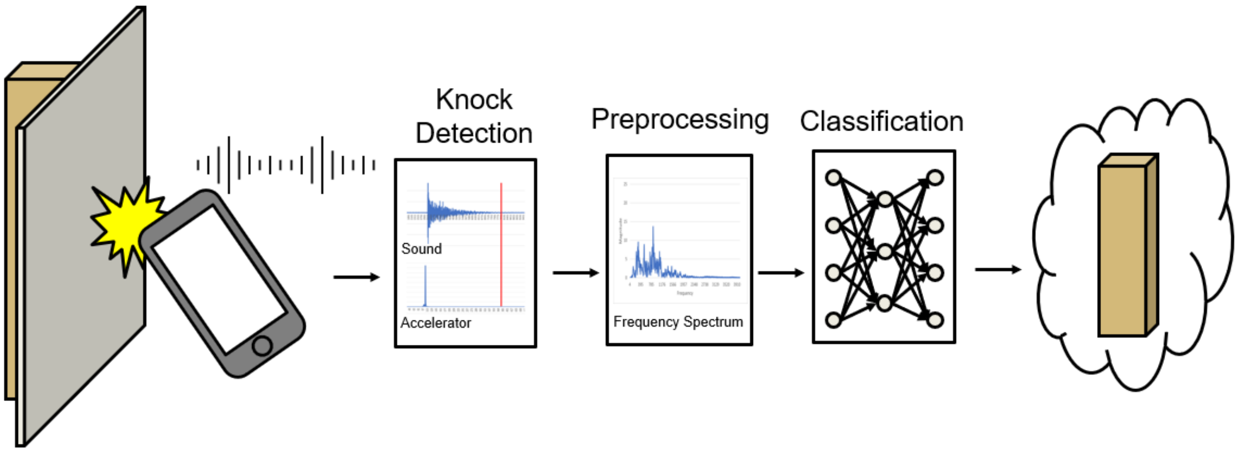


Figure 4.1: DeepScanner system overview.

4.2 Deep Scanner design

Figure 4.1 illustrates the overview of DeepScanner. When we knock on the wall with the smartphone corner, the impact response sound generates. These sounds are collected by the microphone in the smartphone and converted to digital amplitude values with pulse-mode modulation (PCM). Then, using the fast Fourier transform function, we derive the magnitude of its frequency domain spectrum. After normalization, the magnitude of its frequency spectrum is used as an input value of our deep neural network. Finally, the DNN model executes classification with pre-trained parameters and outputs the probability of the stud's existence. Our method consists of three separate phases: knocking sound detection, preprocessing, and classification. The following sections will show each step in detail.

4.3 Knocking sound detection

To obtain the knocking sound fully, we should perform the knocking detection before the knocking sound has started. However, since the knocking sound disperses after a short time (under 80ms), DeepScanner should accurately detect the knocking's start point. In smartphones, there are other sensors besides the microphone. Among them, the accelerator sensor shows a rapid value increase when the phone is shocked. Using this characteristic, we detect at the moment of knocking.

If the acceleration value exceeds the threshold, our system assumes an impact and analyzes the audio signals.

4.3.1 Audio latency

The audio signals collected with the microphone are processed using a buffer of a specific size, resulting in additional audio latency [1]. This delay depends on the buffer size and sampling period. We need a low sampling rate and larger buffer size to maximize the frequency resolution, and this change will increase the latency. Our prototype uses 8000Hz for the sampling rate and 2048 for the buffer size. Theoretically, it takes 256ms to process the knocking sounds. Considering processing time, we designed our system to disregards the audio data after 300ms.

4.4 Preprocessing

We can use several different features to classify different sounds. Among them, to leverage the frequency difference as a feature, we derived the magnitude spectrum using the Fast Fourier Transform (FFT). Contrary to the general trend of VAD (Voice Activity Detection), we did not use the Mel-frequency Cepstral Coefficients (MFCCs) for features. The purpose of MFCCs is to use filters to obtain sounds more similar to that of a human ear's hearing. Our intuition is that human ears cannot discriminate between knocking on a stud versus a non-stud; we used the magnitude spectrum itself. We normalized the acquired magnitude spectrum because the magnitude values correlate with the amplitude of the sound. According to the Nyquist-Shannon sampling theorem, as our sampling rate is 8000hz, we can get the frequency spectrum from 0 to 4000Hz and this frequency range is divided and saved into 1024 blocks.

Chapter 5

DEEP LEARNING BASED CLASSIFICATION

5.1 Data collection

Figure 5.1: Residence buildings for data sampling: townhouse, apartment, single-family.

We collected knocking sounds from three different types of residential buildings for our deep learning-based stud finder: a townhouse, apartment, and single-family house. We sampled the wall every 4 inches horizontally for a 16-inch difference between the two studs. We measured the wall 36 to 60 inches up from the floor with a 6-inch gap vertically. For each sample point, we collected around 400 samples and collected 30,000 samples in total.

5.2 Classification

5.2.1 DNN design

Unlike other conventional machine learning classifiers such as random forests or SVMs, the benefit of deep neural networks (DNNs) is that it does not need human interference to extract features. The DNNs can find features from the input data by themselves while training and classify them. Furthermore, deep learning offers the probability of each classification directly. We can utilize this probability to estimate the existence of a stud.

Convolutional neural networks (CNNs) are now the primary tool for deep learning for their performance. This is because they offer feature extraction and classification from raw data. Besides, they are immune to input data transformation like translation, skewing, and distortion. Thanks to these benefits, recent CNNs are used for sequential one dimension data such as biomedical data classification, early diagnosis, and anomaly detection. Relatively low computational requirements compared with 2D CNNs, 1D CNNs are well-suited for real-time and energy-efficient applications required on a mobile device.

Considering these advantages and our collected data having one-dimensional data form, we decided that 1D CNN is the best to infer the existence of a stud using collected knocking sounds. Therefore, we designed a compact 1D CNN with the following architecture: 1 convolutional layer with filter width of 5 by 64 neurons of Relu activation function plus a flatten layer and one softmax layer with two outputs.

5.2.2 Classifier

The softmax layer converts a vector to a vector of categorical probabilities. The elements of the output vector are in the range 0 to 1 and sum to 1. With this characteristic, we chose softmax activation in our supervised classification. We used the output value of 1 as the probability of the existence of a stud.

5.2.3 Training model

We collected 30,000 magnitude samples from 3 different residence buildings with a Pixel XL Android Phone for training our machine learning models. We labeled the samples collected over the stud with 1 and samples collected between the studs with 0. After the labeling, we implemented and conducted training on the Google Colab server.

5.2.4 DNN evaluation

While training the DNN on the Colab, we took 25% of the entire sample set as a test set and calculated each epoch's accuracy. The hyperparameters of our DNN are as follows: batch size: 32, number of epochs: 50, activation function: Relu, and optimizer: Adam. With those parameters, our DNN accuracy reached up to 97.5% (Recall: 0.95 and F1_score: 0.96).

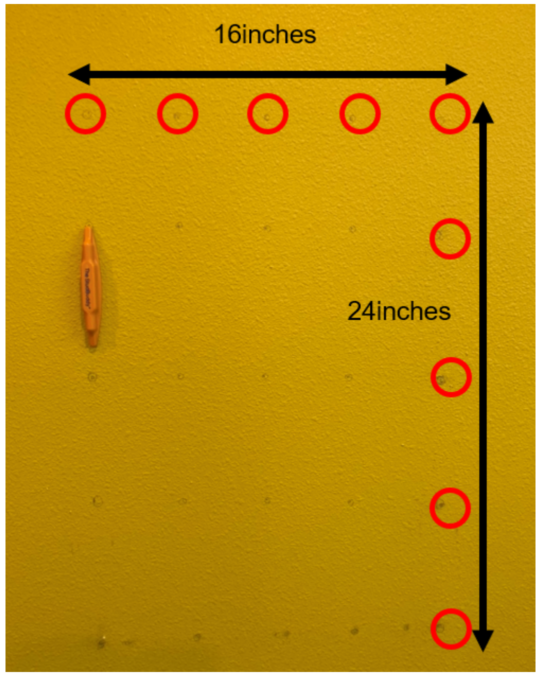


Figure 5.2: Sampling description.

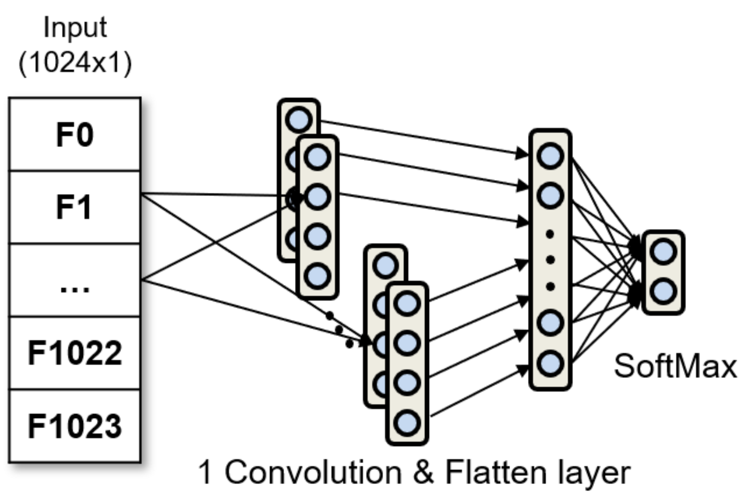


Figure 5.3: 1D-CNN design.

Chapter 6

ACCURACY IMPROVEMENT

Even though our DNN models are well trained and show high accuracy, it has a fundamental problem that the training data have 4 inches of the interval; there is an accuracy problem that arises. The general wooden stud's width is 1.5-inches which means we have to find the middle of the stud within an accuracy of 0.75 inches. To test the accuracy around the stud, we marked two inches on the left and right of the studs at intervals of half an inch. Then, we knocked on the wall 50 times for each mark with a smartphone and counted how many times the device shows stud existence. We assume a stud exists on the knock point when the DNN output value is over 0.9 out of 1. Figure 6.1 means the probabilities around the stud. This graph shows that our approach misclassifies a stud even at a location greater than 0.75 inches from the stud's center.

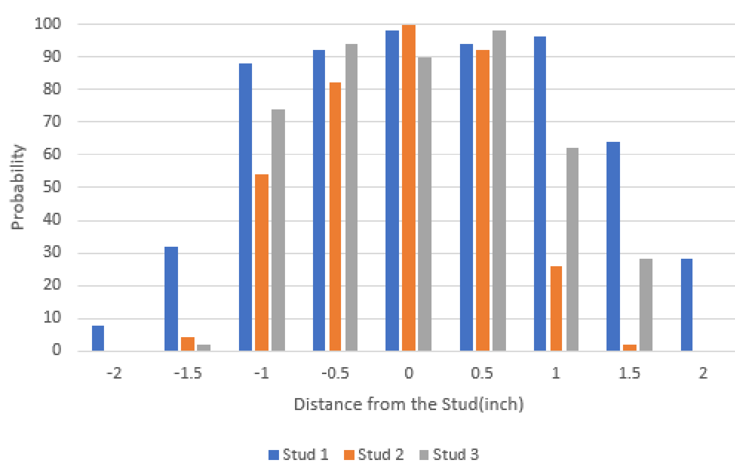


Figure 6.1: Probability around the stud.

6.1 Accuracy dilemma

To achieve high accuracy, the user may have to knock numerous times. However, hitting the wall several times can be burdensome for users and harm the wall finish. But if the user knocks less, there could be more errors in finding a stud location. Although, as shown in Figure 6.1, the highest probability does not always guarantee the stud's center. In some cases, we can see a high probability even out of the stud.

6.2 Error correction

We observe that probabilities of the left and right sides of a stud are symmetrical, which we exploit to find an exact location of a stud. While our approach does not require a user to knock multiple times on the same spot, a user needs to knock a relatively small region when it finally finds the center of a stud. Using this human-in-the-loop approach, we can find the center of a stud more precisely.

Chapter 7

EVALUATION

We implemented the DeepScanner application on an Android device and evaluated the performance of DeepScanner in two scenarios.

7.1 Implementation

We implemented our DeepScanner application on Android devices. When the SensorEventListener function detects the abrupt increase of accelerator value, the AudioRecord class collects the raw sound in 16-PCM values and processes it with a fixed size buffer. Then, the FFT function transforms the raw sound to magnitude spectrum for frequency. We implemented our trained DNN model using TensorFlow-lite and used the magnitude spectrum as the input data. For each knock, our DNN model returns the output values of the prediction for the classification. The default setting shows "No Stud" until the prediction value indicates the existence of a stud. Based on this internal mechanism, our DeepScanner has two phases to find the stud: wide scanning followed by deep scanning.

7.1.1 Wide scanning

In the wide scanning mode, a user finds a rough location of a stud; the user knocks randomly along the imaginary horizontal line. While scanning the wall, our DeepScanner starts indicating a stud frequently at some point. In this case, the user moves to the following phase.

7.1.2 Deep scanning

After a user found the stud's existable area in the wide scanning mode, a user switches to the deep scanning mode to find the exact stud location, where a user hits multiple times. During this process, our DeepScanner instructs the user whether to move forward or backward.

7.2 Ground truth

In all experiments, including training, we found the ground-truth location of a stud using a combination of an electronic, radar, and a magnetic stud finder. Figure 7.1 shows stud finders used in this research. For example, the HD70 from the ZIRCON corporation is a center finding stud finder with an accuracy of within 3mm of the center [22]. The Walabot is a radar-based stud finder that can render behind the wall, such as studs or pipelines. We also used a magnetic stud finder to find the metal screws on the studs to verify the stud location.

Figure 7.1: Stud finders used for finding a ground-truth location of a stud: electronic stud finder (HD70), radar stud finder (Walabot), and magnetic stud finder (StudBuddy).

7.3 System evaluation

We evaluated the performance of DeepScanner for two different scenarios: noise environment and field test.

7.3.1 Scenario 1: noise environment

We conducted the test in the apartment where we collected data. We chose a cinema room in the apartment as a test site because it is located in a noise-free space and equipped with user-adjustable speakers. For the noisy environment, we have played a movie while we execute the test. The ambient sound measured around 65dB as shown in Figure 7.2. Note that 60dB is the noise level of normal conversation and 70db is that of a washing machine [6]. We tested without noise first and then with noise for comparing the results.

Figure 7.2: Scenario 1: noisy environment.

Evaluation result Figure 7.3 shows no significant difference in the accuracy with the presence of noise. The result shows no significant difference in the accuracy with noise. We can tell that they are both within the acceptable deviation under 0.75 inches.

7.3.2 Scenario 2: field test

In Scenario 2, we tested from the three different residential buildings where we did not collect samples for training: a dormitory, a hotel, and an attached house as shown in Figure 7.4. We executed the test on walls which we ensured that interior walls were built with gypsum board and wooden studs with screws.

Evaluation result Figure 7.5 shows that our model can apply to other residence buildings. Scenario 2 shows a little larger variation than Scenario 1. Except for one case from the attached house

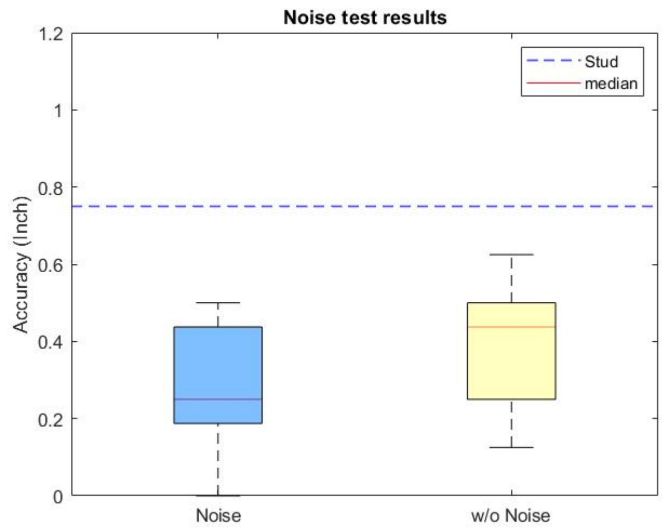


Figure 7.3: Result of scenario 1.

of 1-inch deviation, all the result values from three residence buildings are under 0.75 inches.

7.4 Result

The DeepScanner shows less than 0.75 inches of accuracy from the stud center in various situations. From Scenario 1, we found that DeepScanner works in a noisy environment without a performance decrease. We attribute this result to two reasons. First, the knocking sound is dominant over the ambient noise because the knocking spot is relatively close to the microphone on the smartphone [9]. Second, the typical conversation frequency range is approximately from 100Hz to 300Hz, relatively narrow compared with the frequency spectrum used for knocking. From Scenario 2, we can see that DeepScanner works on other residence buildings with similar accuracy under 0.75 inches even the training is done with some other walls. Considering the typical stud's width is 1.5 inches, our DeepScanner's performance is satisfactory.

Figure 7.4: Residence buildings for field test: attached house, hotel, dormitory.

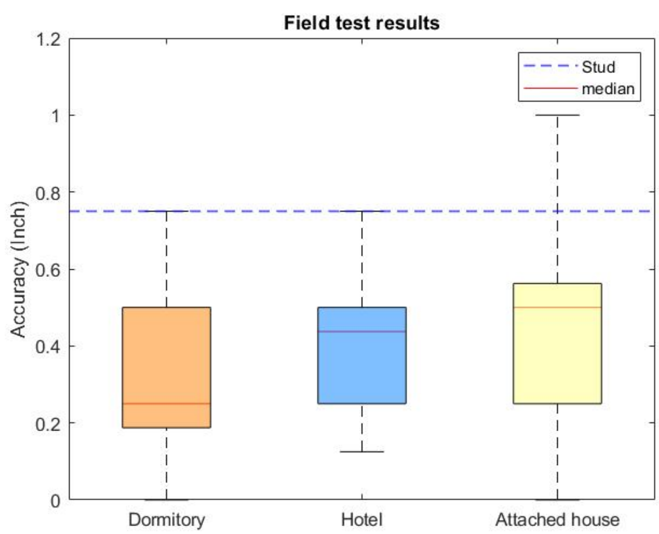


Figure 7.5: Result of scenario 2.

Chapter 8

DISCUSSION

In this section, we discuss the limitations of DeepScanner and further applications.

Wall limitation. Our research assumed that the wall is constructed only with wooden studs and gypsum board without other materials. Most interior walls are made up of those materials, but exterior walls have insulation to prevent water infiltration and increase thermal performance and fire resistance. We observed that this insulation affects the performance of the DeepScanner. Also, one must consider the inside of the wall, where there could be pipes or wires located. Because generally they are settled right beside the stud, this can also distract the performance DeepScanner.

Compatibility to other smartphone. Because of the different weights and body materials, each smartphone's knocking sound can differ from the collected data. In our test, Galaxy Note 9 shows similar accuracy with Pixel XL. However, Galaxy Note 4 couldn't find the stud with our application. The main difference between these smartphones is that Pixel XL and Galaxy Note 9 used aluminum for the body frame, but Galaxy Note 4 used plastic, as shown in Figure 8.1.

Other applications. We focused on finding studs behind the wall utilizing the frequency difference. This approach can be applied in various ways. For example, when a wooden stud gets wet and starts to rot, its properties will change over time. If we find a stud that reacts differently in the same house wall, we could find a rotted stud without visually inspecting the wall.

Figure 8.1: Different materials for frame body: Pixel XL(Aluminum), Galaxy Note9(Aluminum), Galaxy Note4(Plastic).

Chapter 9

RELATED WORK

9.1 Using impact response for object recognition

Giving an external shock on an object and listening to the response can deliver important information about the material. Intuitively humans have used this technique for a long time for sensing qualities of a material. For example, when buyers check a watermelon for ripeness, they normally thump the watermelon. Because of the advantage of not breaking an object, similar approaches using impact response have been used to determine fruit quality. Such as the coconut [2], melon [12], and mangifera[19]. However, they need a specifically designed sound module to collect the response sound. After the smartphones embedded with various sensors became prevalent, there were novel attempts using smartphones. Zheng et al. [20] use the sound generated from thumping watermelons and collect acoustic signals with microphones on mobile devices. They achieved 89% accuracy in classifying watermelon ripeness. Knocker [10] utilized the microphone, gyro-meter, and accelerometer sensors in the smartphone to identify the objects by knocking on the materials. It achieved 98% accuracy with 23 objects. However, their objects had significant material differences, such as plastic, wood, metal, paper, and glass. Also, they used the same objects for both training and evaluation. Our DeepScanner builds a generalized feature from the wall and tests it in different locations for validation.

9.2 Other object recognition approaches

Besides sensing impact response, there have been a variety of approaches in object recognition. For example, using a backscattering signal from the UHF RFID tag, Jinsong et al. [11] detected moving objects with errors of 0.75m. In addition, Caizzone et al. found the sub-millimeter deformation of an object by utilizing the coupling phenomenon between two RFID tags [5]. Since there is widespread installation and active sensing ability, WIFI-based approaches have been developed. For example, the research by Bao et al. [21] detected the metal and liquid concealed by a pedestrian with an accuracy of 93.3% using WIFI. LLAP[18] uses ultrasound to trace hand gestures with an accuracy of 3.5mm for 1D movement and 4.6mm for 2D movement.

Chapter 10

CONCLUSION

The DeepScanner is a deep learning-based stud finder that leverages real-time sound in a smartphone. Unlike traditional methods using custom systems for an impact-audio response, DeepScanner uses a microphone embedded in the commodity smartphones without any specialized equipment. Using a 1D convolution neural network with two hidden layers, DeepScanner achieved 97% of accuracy from the training samples and found the stud with an accuracy of 0.75 inches. As anyone with a smartphone can use DeepScanner, we expect people to use it easily and conveniently in various ways.

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