USAGE OF WIFI CSI FOR THROUGH-WALL MOISTURE LEVEL CLASSIFICATION

THESIS

Submitted in Partial Fulfillment of

the Requirements for

the Degree of

MASTER OF SCIENCE (Mechatronics and Robotics)

at the

NEW YORK UNIVERSITY

TANDON SCHOOL OF ENGINEERING

by

Shivam Joshi

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Approved:

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Advisor Signature

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Date

_____
Department Chair Signature

_____
Date

University ID: **N18161200**
Net ID: **sj3104**

Vita

Shivam Joshi was born in Indore, India. He received his Bachelor of Engineering in Mechanical Engineering from Madhav Institute of Technology and Science, India, in May 2017.

Since 2019, he has been engaged in the Master of Science in Mechatronics and Robotics Engineering at New York University, Tandon School of Engineering in Brooklyn, New York. In Early 2020, he joined the AI4CE group headed by Prof. Chen Feng. Since then, he has spent time working on robot navigation, computer vision, unsupervised tracking, and machine learning in general. His interests extend to Robot Perception, deep learning and the intersection of Civil Engineering and Robotics.

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To my parents and Piyu

ABSTRACT

USAGE OF WIFI CSI FOR THROUGH-WALL MOISTURE LEVEL CLASSIFICATION

by

Shivam Joshi

Advisor: Prof. Chen Feng

Submitted in Partial Fulfillment of the Requirements for the Degree of Master of Science (Mechatronics and Robotics)

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As the requirement for moisture measurement devices is rising in construction, forest and food procurement industries, researchers are coming up with innovations and advancements to solve this problem. In the construction industry moisture meters are being used at sites for forensic work by inspectors, supervisors, engineers and vendors working on-site. Ability to classify walls into safe and unsafe categories depending on the moisture content within and doing so at a low cost could boost the productivity at the site and at the same time ensure that quality construction is being done.

Most of such devices and through-wall systems use radio technologies to solve the problems. Through-wall systems are now being used to solve multiple problems in robotics ranging from presence detection, localization, navigation, human identification/authentication, grasping hidden objects, etc. A growing field of research in robot perception is usage of WiFi-based systems to solve

these problem. WiFi-based systems mainly have three approaches:

1) Analysing the Received Signal Strength (RSS),

2) Analysing the Channel State Information (CSI), and

3) Analysis of WiFi signals through software defined radios (SDR).

In this work, we have collected WiFi CSI from the physical layer for creating the datasets for different CSI measurements corresponding to different moisture levels of plywood walls. Later, we have trained neural networks in order to classify plywood walls as safe or unsafe as per the moisture content in them from the construction perspective.

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List of Abbreviations

LOS	**L**ine **O**f **S**ight
CSI	**C**hannel **S**tate **I**nformation
RSS	**R**eceived **S**ignal **S**trength
SS	**S**patial **S**treams
MC	**M**oisture **C**ontent
OFDM	**O**rthogonal **F**requency- **D**ivision **M**ultiplexing
WLAN	**W**ireless **L**oal **A**rea **N**etwork
Tx	**T**ransmitter
Rx	**R**eceiver
RF	**R**adio **F**requency
BW	**B**andwidth
NN	**N**eural **N**etwork
RTI	**R**adio **T**omographic **I**maging
SDR	**S**oftware **D**efined **R**adio
FMCW	**F**requency **M**odulated **C**ontinous **W**ave

Chapter 1

Introduction

In this work, we propose to use Wi-Fi CSI for through-wall non-destructive moisture content measurement. Similar to [1] and [2] we have relied on CSI amplitudes in our data to solve this problem. A difference between CSI amplitudes and phase is shown in figure 1.1 for one of the packets with the WiFi channel 36 (5180 MHz center frequency) and 80 MHz bandwidth in the 5 GHz range.

CSI contains the frequency response of a communication medium. This response is sensitive to the changes in the environment. If we analyze the CSI of Wi-Fi frames at the receiving end, slightest modifications in the medium can be spotted with high probability. Wi-Fi standards 802.11a and beyond supports Orthogonal Frequency-Division Multiplexing (OFDM). OFDM is at the core of using channels frequency response. Contrasting to RSS which is a cumulative signal strength indicator at the receiver, CSI between one pair of Tx-Rx antennas contains both the signal strength and the phase information of each OFDM sub-channel.

In our work, we focus on the MC based classification using CSI amplitudes. In our experiments, we collect CSI amplitude and phase data on two different levels of MC: less than 15% and more than 15% and label them as safe and unsafe respectively. The MC level of 15% was chosen as per the conclusions

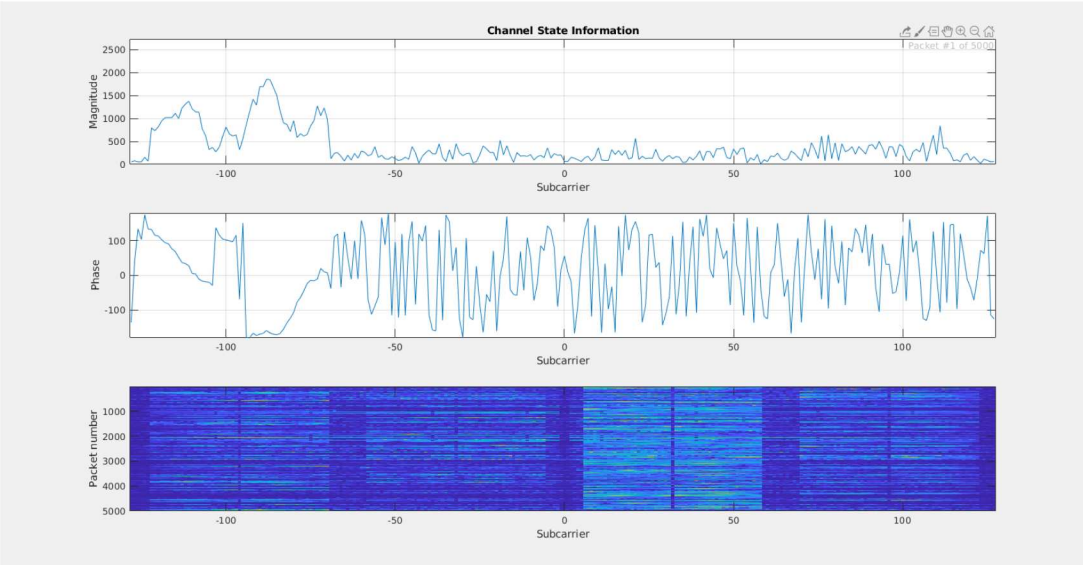

FIGURE 1.1: Amplitude and Phase for a single CSI packet

made in [3] and [4].

A majority of plywood MC levels have different values of CSI amplitude and/or phase difference. However, these are still very close to CSI values for different plywood MC levels, which makes this classification difficult. With the assistance of deep learning techniques we have created a ResNet [5] based classifier [6] for achieving high classification accuracy. We take amplitudes of WiFi signals corresponding to safe and unsafe material quality and use it to train the network. Research works based on deep networks similar to this have shown great results in biometrics estimation (fat and water content), person recognition, sign recognition and fall detection. [7]

1.1 Motivation

A lot of research has been done in the field of moisture measurement for building materials [8] including plywood [9], and adverse effects because of it have been well documented [10]. However, the construction industry still relies on

expensive ground penetrating radars or inaccurate and highly sensitive moisture meters to identify and tackle problems in practice. The key driving factor behind our work is to find an innovative and ubiquitous solution for MC based classification of materials into safe and unsafe categories. By looking at the latest research work pertaining to robot perception and biometrics estimation, we had an instinct that the usage of RF signals coming from modern WiFi devices could give us results we are looking for. We have also looked into developing our own SDR based setup for through wall perception tasks inspired by plentiful research [11] [12] [13] in that area. However, to keep the system simple and cost low we decided to move ahead with the option of WiFi based RF signals for our work.

An essential catalyst in developing novel WiFi sensing techniques is the availability and feasibility of tools [14] [15] for measuring Channel State Information (CSI). We have used a flexible and powerful CSI extraction tool for modern Wi-Fi chipsets: nexmon-csi tool [16] for our work.

1.2 Contribution

The goal of this work is to suggest a novel and simplified solution to the moisture level classification problem. Multiple WiFi CSI datasets are collected and transfer learning is performed using a base neural network model [6] - CSI Net. This network is tweaked to perform classification instead of estimation that it was initially designed for. Key contributions of our approach are as follows:

1. We have created diverse dataset for channel 36 at 5GHz WiFi frequency band with 20MHz, 40 MHz and 80MHz channel bandwidths. Further, data is collected for 1x1, 2x2 and 3x3 Spatial Streams for each of these channel

bandwidths. This gives us a set of 9 rich WiFi-CSI datasets dedicated to the task of moisture level classification.

2. We propose a deep learning based method to perform the classification of safe/unsafe plywood walls according to their mechanical properties virtue of moisture content within. [3]

3. A step-by-step guide in a blog format is provided for anyone interested in this area of research using the nexmon tool [17] to collect CSI data using WLAN routers.

1.3 Outline

Rest of the thesis provides details on creating a through-wall system for MC level classification task. We have tried to put forth a descriptive and healthy discussion on all the underlying concepts and techniques. To attain this the body of work is organized accordingly.

Chapter 2 gives an holistic scope of RF sensing techniques pertaining to this work and for robot perception in general. This section provides a broad overview of methods available and research efforts dedicated to solve similar problems as usage of WiFi CSI for MC based classification.

Through Chapter 3, we have tried to provide as much preliminary knowledge as required to understand this work. Most of the details are related to RF signal behaviour, WiFi CSI matrix concepts. Further, latest trends and structure for CSI based WiFi sensing approaches are mentioned. Moreover, challenges related to usage of WiFi CSI are discussed to enable a deeper perspective in the reader for the subject matter.

Chapter 4 forms the core of this work. We have enumerated all the valuable specifics that are required to create a similar system or to repeat the findings this work mentions. This chapter starts with the details about the physical setup used for the data collection process for this work. Then information about the software tools and resources used for the purpose of gathering CSI packets is provided. A brief overview of the data manipulation, cleaning and storing with structure of final dataset files is mentioned in the next section. Following section gives specifics about the neural network architecture used for training the classifier. The chapter ends with particulars on training and testing the network.

Once the whole methodology for experimentation is explained, Chapter 5 intends to demonstrate the results achieved from the trained binary classifier. It also mentions the datasets created and provides links to access the code for creating datasets and links to datasets saved on github.

Finally, Chapter 6 concludes the paper and provides some proposals for further advancements that could be made in this work going forward.

Chapter 2

Related Work

The research work and survey papers involving WiFi CSI based sensing heavily focus on the mainstream robot perception problems including localization, tracking, activity recognition, health-monitoring, etc. This posed a difficulty for us in finding relevant research involving targeted solution. Further, most of these solutions are for direct measurements of CSI in the medium, without involving walls. While search for through-wall sensing solutions, we found some great research works [18] but these were also diverging from the purpose of MC level estimation or classification. Some notable works from agriculture industry [19] [20] involving moisture content based classification in wheat and wooden logs motivated us to continue with our work. In the following sections we have tried to categorize RF sensing research for through wall scenarios and research involving WiFi CSI in general. Eventually, we have also described works that helped us to converge for finding a WiFi CSI based MC levels classification solution.

2.1 Through-Wall Systems

Through-wall sensing systems can be categorized into four categories:

1. WiFi-based system

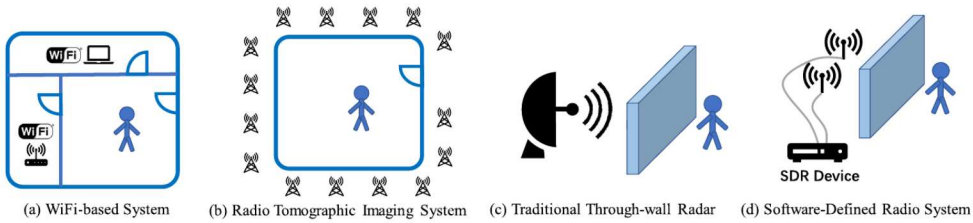

FIGURE 2.1: A brief illustration of the setup of the four categories of through-wall systems.

2. Radio tomographic imaging (RTI)

3. Traditional through-wall radar

4. Software defined radio (SDR) system

Figure 2.1 represents a generic setup for these four categories. [18] In this (a) depicts the generic setup for WiFi-based systems. These systems measure fluctuations in channel because of changes in the medium. (b) shows the idea behind radio tomographic imaging (RTI). Signal strength between all pairs of sensors is measure in a dense sensor network to gather information pertaining to medium changes. (c) represents the classic approach for traditional through-wall radar. (d) depicts a simple representation of the software-defined radio (SDR) system. These systems use multiple Tx-Rx antennas and process received signals by SDR devices, e.g., USRP and personal computers.

2.1.1 WiFi-based system

Ubiquitous presence of WLAN devices and latest advancements involving multi-user MIMO and OFDM in 802.11 technologies [21] have paved the way for using WLAN devices like APs and home routers for perception and RF-based sensing research. Digital signal processing and/or machine learning techniques are common to get results in almost all the WiFi based sensing research. Consequently, this technology can be classified by the the type of inputs used to solve

the sensing problem. There are mainly three approaches to categorize the WiFi-based systems broadly:

1. Based on RSS from the MAC layer
2. Based on CSI from the physical layer
3. Analyzing WiFi signals through software radio technology.

RSS indicates the received signal power measured using one or more packets transmitted using WiFi. RSS-based systems inspect the pattern of varying RSS. An alternative is to use the signal-to-noise ratio (SNR) for similar pattern recognition. These systems are commonly used for localization [22] [23] tasks. In the through-wall scenarios these systems have been shown useful for imaging purposes using robots and drones [24] [25].

CSI characterizes more detailed information about the WiFi channel in comparison to RSS. Usage of CSI for perception and sensing tasks has gained a lot of popularity [26] [27] lately. The application areas inlude tracking [28], health-monitoring [29], localization [30] [31] [32], motion detection [33] [34] [35], gesture recognition [30], and activity recognition [36] [37] [38].

Finally, the approach underneath software radio scheme is to use the universal software radio peripherals (USRP) to process WiFi signals. An alternative is to use wireless open access research platform (WARP) to fabricate custom WiFi systems. Some through-wall solutions include gesture recognition [39]. However, since these systems can also be categorized as SDR systems, we have included other applications in section 2.1.4.

2.1.2 Radio tomographic imaging

RTI is an growing method [40] [41] involving reconstruction of the spatial loss field of the medium through a dense sensor network [42]. Particularly, RTI

systems evaluate the spatial accumulation effect the RSS loss to map the environment. This is done relying on a large number of sensors around the target area [43] . RTI is an impacting technique for through-wall detection problem and the setup for this type of solution is cost-effective as well. [44]

2.1.3 Through-wall Radar

Through-wall radar is part of a mature technology and is well-studied because of its applications mainly related to military. These radar have following categories:

1. Ultra-wideband (UWB) radar
2. Doppler radar
3. Frequency Modulated Continuous Wave (FMCW) radar.

Among these categories, UWB radars are most common virtue of its high range and penetrability. However, all these radar classes have an edge over other through-wall technology that these systems are not affected by some critical challenges in through-wall scenarios. But on contrary, these systems are expensive, bulky and power-consuming.

Some research works involving UWB radar in construction focuses on layout reconstruction [45]. Most of the other works solve human detection [46] [47] and positioning [48] problems. Doppler radar has been used for through-wall biometrics estimation [49] along with environment sensing [50]. Similarly, FMCW radars are also used to measure through-wall bio-metrics information [51] along with some tradition imaging tasks [52].

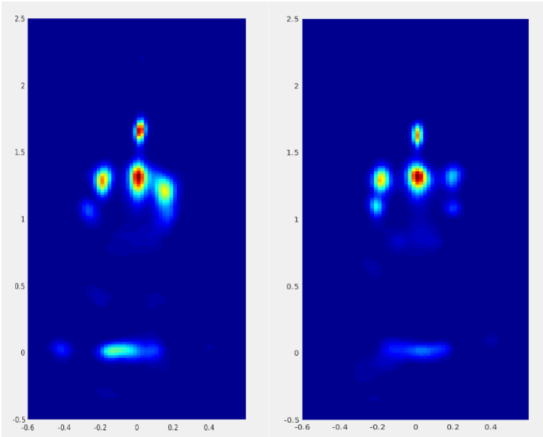

FIGURE 2.2: RF-Pose replicated image

2.1.4 Software Defined Radio

A common approach in RF field is replacement of hardware components with software tools. This gives more control and greater feasibility to modify systems. However, this advantage comes with an additional requirement of specialized RF devices (e.g. antennas, PCBs, RFIDs, etc) and specialized software platforms (e.g. USRP).

RF-Capture, by Adib *et al.*, utilizes both FMCW and USRP concepts for through-wall imaging [12]. This device forms the basis for multiple research works using a similar device in numerous application areas. There are msny other systems [13] [53] for through-wall imaging along with RF-Capture.

SDR-based systems are very effective for localization [54] [55] [56] and human vital signals detection [57] [58] as well.

RF-Pose [13] and RF-Pose3D [59] proposed by Zhao *et al.*, can create a 2D or 3D model of a human body through RF signals. This work was replicated by us while carrying out the literature review for this thesis. An example of the saved image from our replication of this work is shown on figure 2.2

2.2 WiFi Based Methods for Moisture

Most of the research for estimating moisture content comes from the agriculture industry. Apart from off-the-shelf moisture meters, agriculture industry incorporates application specific methods [60] that can be used for this purpose. Further, new advancements in robotics have also been exploited in some of the works [61]. Further, some of these solutions also involve usage of CSI data for MC estimation as done for Wi-Wheat [62] by Yang *et al.*

Similarly, in the construction industry most of the popular research for estimating or classifying on the basis of MC is based on tradition electrical methods [63] [64]. Some papers that were most aligned with our area of interest tried to detect MC [65] or categorize wood into multiple categories based on MC [66]. We would also like to mention WiHumidity [67] by Zhang *et al* as it also closely relates to our work.

Chapter 3

Background

WiFi has gained a rapid growth with increasing popularity in wireless networking. An important contributor to this is the principle of Multiple-Input Multiple-Output (MIMO) that provides high data throughput for increasing demands. OFDM and MIMO together provide CSI for each Tx-Rx antenna pair for each carrier frequency. As this method re-utilizes the infrastructure created for wireless communication, it has a low cost with ease of implementation. Below we provide some preliminary knowledge on concepts required to understand this area of research.

3.1 RF Physics

RF signals are electromagnetic waves ranging in the frequency range of 3 GHz to 300 GHz. These waves are longer than infrared light range in terms of wavelength. Electromagnetic (EM) waves have 7 important properties:

1. Attenuation: Gradual loss in power
2. Amplification: Power gain, externally
3. Reflection
4. Refraction
5. Absorption

Material	Dimension (cm)	Loss (dB)
Wallboard	1.2 × 121.8 × 196.9	0.45
Cloth Partition	5.9 × 140.7 × 153.1	2.55
Structure Wood	2.1 × 121.5 × 197.8	1.35
Styrofoam	9.9 × 121.8 × 197.7	0.10
Concrete Block	19.45 × 39.7 × 19.5	13.6

Frequency of the transmitted signal: 5 GHz

FIGURE 3.1: Attenuation through different materials

6. Scattering

7. Diffraction

Attenuation is inversely correlated to transmission. Transmission, absorption and reflection are key properties that facilitate EM waves to be widely used in the through-wall technology. Some information on these basic principles is as follows:

Transmission levels of the EM wave are dependent on the frequency. Particularly – higher the frequency, lower the transmission performance. This property results in a low-pass filtering effect when passing through an obstacle. For example, visible light with higher frequency cannot penetrate through brick walls but RF can.

Further, **absorption** also plays an important role in signal transmission. Absorption of wave is dependent on the type of material. Materials like wood and drywall have a small loss, whereas brick walls have huge loss. Figure 3.1 shows attenuation of signals through different materials. Further, figure 3.2 shows attenuation of signals with different frequencies [68] [18] across bricks. Water also absorbs RF signals and in this work we are trying to exploit this very property of RF waves.

RF also **reflects** on encountering obstacles such as humans, walls and/or furniture. Through-wall systems exploit this property to calculate distance and angle of these objects. Since, reflected signals may have a lot of noise, some

Frequency (GHz)	Loss (dB)
1.01	2.06
1.91	3.02
3.11	4.30
4.01	5.27
5.21	6.55

Material: Bricks, 8.7 cm × 19.8 cm × 5.8 cm

FIGURE 3.2: Attenuation with different frequencies

filtering methods are mostly needed.

3.2 CSI Principles

WiFi is broadly split into two categories based on the frequency range used to transmit the information - 2.4 GHz band and 5 GHz band. The 5 GHz band is a name tag for the RF signals used to transmit WLAN data with frequencies ranging from 5030 MHz to all the way up to 5895 MHz frequency. For the purpose of sub-categorizing this whole range of frequencies IEEE 802.11 standards are used. This standard provides protocols as well as distinct RF ranges for the purpose of WiFi communication. Each of these ranges is further divided into a multitude of channels. The channel split and naming for the WiFi 802.11ac standards can be seen in figure 3.3.

Further, each WiFi channel is then divided into multiple sub-carrier frequencies as a result of of MIMO-OFDM. This is done for optimized communication and avoiding information overlap. A WiFi channel split into subcarrier frequencies is depicted in figure 3.4.

CSI is characterization of wireless (RF) signals propagation in a medium from the transmitter to the receiver at certain carrier (channel) frequencies. The properties we discussed in previous section result in a change of CSI amplitude

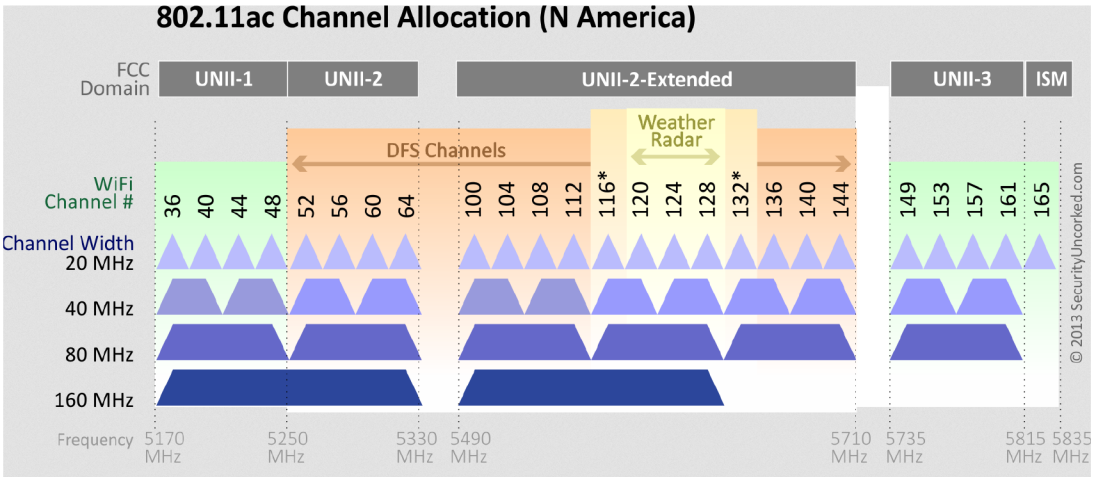

FIGURE 3.3: WiFi 802.11ac channel allocation in North America.

and phase shift due to multi-path effects, attenuation, absorption and reflection. Each CSI entry represents the Channel Frequency Response (CFR):

$$H(f,t) = \sum_{n}^{N} a_n(t) e^{-j2\pi f \tau_n(t)} \tag{3.1}$$

where $a_i(t)$ is the amplitude attenuation factor, $\tau_i(t)$ is the propagation delay, and f is the carrier frequency. The CSI amplitude $|H|$ and phase $\angle H$ are influenced by the changes in the medium including movement of Tx-Rx or surrounding objects and humans.

To measure the CSI information, a WiFi Tx sends Long Training Symbols (LTFs), having pre-defined symbols for each subcarrier. This is sent through a packet in the packet preamble. When LTFs are received by the Rx, it estimates the CSI matrix comparing received signals and the original LTFs.

For these subcarriers, the WiFi channel is modeled as follows:

$$y = Hx + n, \tag{3.2}$$

Where y is the received signal, x is the transmitted signal, H is the CSI matrix, and n is the noise vector. Once the received signal is processed by a Rx router,

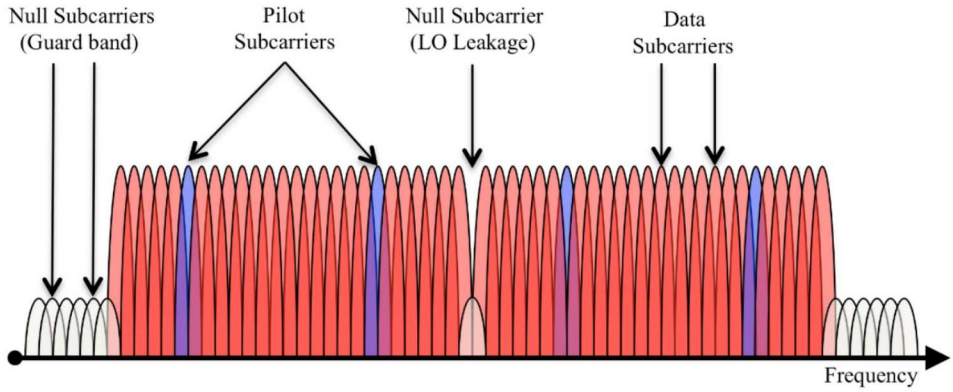

FIGURE 3.4: Illustration of subcarriers for a single WiFi Channel.

CSI matrix is calculated as a three dimensional matrix of complex values. Figure 3.5 shows the 4D CSI tensor is a time series of CSI matrices of MIMO-OFDM channels. It captures multi-path channel variations, including amplitude attenuation and phase shifts, in spatial, frequency, and time domains. [7]

3.3 Challenges of through-wall technology

As we discussed in the first section of this chapter, RF has some properties that make them a great resource to be used for through-wall scenarios. However, there are some natural disadvantages of using RF too which pose some engineering challenges to us. Some of these challenges are motioned below:

1. **Multipath Effect:** If the CSI data is collected in a changing and complex environment, it would result in multipath effect. This will only get worse if the application requires to focus on more than one target locations within the experiment environment. Multipath is worse in the indoor setups because of walls, humans and other obstacles in near vicinity of the Tx-Rx. Further, indirect signals coming from different locations can result in accurate CSI estimations and hence degrading the performance of intended

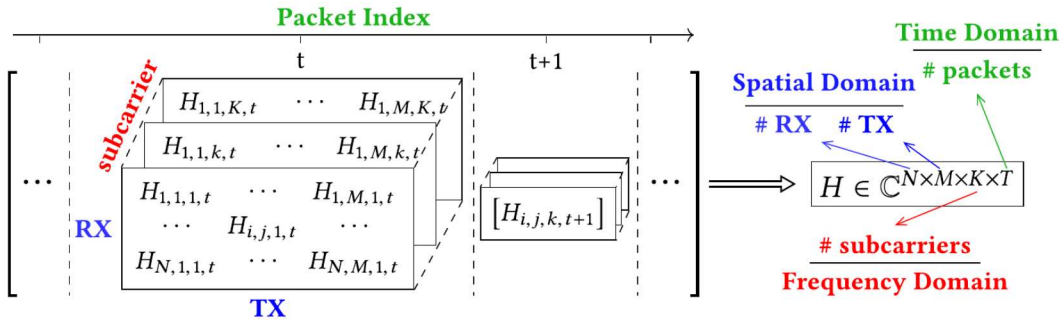

FIGURE 3.5: 4D CSI tensor

through-wall system. To resolve this issue MUSIC [56] algorithm, similar solutions [69] [70] can be used.

2. **Mirror Effect:** Because of the size of the obstacle, some CSI signals would be reflected instead of scattering. It is noteworthy that scatter is more useful because of the visibility in all directions compared to reflection which is directional. This mirror effect [71] can result in only a proportion of reflected signal to be received at the Rx.

3. **Measurement Errors:** Analog-to-Digital Converters (ADCs) are used for digitize the analog RF signal coming at the antennas. Since these RF signal have a very high transmission speeds, sometimes it is difficult for ADCs to accurately measure certain signal parameters like Time-of-Flight (TOF). Using high accuracy ADCs could be expensive in terms of cost and power consumption. To tackle this following techniques are used:
   1. Usnig FMCW to measure the TOF.
   2. Calculating the direction of arrival (DOA) instead TOF
   3. Using the RSS or CSI pattern to achieve localization.

4. **Attenuation:** While experimenting for a through-wall system, transmitted signal can lose the essential information because of attenuation through obstacles and walls. Higher frequency can result in higher resolution of

the information but it is also prone to more attenuation. Hence, it is a challenge to know what frequency ranges of RF signal would work the best for the task at hand.

Chapter 4

Methodology

The dataset that we have collected and MC classifier created required an all-inclusive effort. This includes physical setup consisting of two WiFi routers utilized as Tx and Rx pair. Further, plywood pieces with different MC are used while gathering the data. The data collection itself requires efforts in MATLAB and Python programming and firmware patching on these off-the-shelf WLAN routers. And finally, everything was put in place by training the classifier and getting meaningful results out of it. Following sections discuss the methods and dives deeper in the experiment design. A typical flowchart for WiFi sensing framework is shown in the figure 4.1 [7]

4.1 Physical Setup

The critical elements of the through-wall MC classifier setup are two WiFi Router used for capturing WiFi CSI at the UDP transport layer. We have used Asus Routers - Asus RT-AC86U [72] as they use Broadcom Wi-Fi Chips (bcm4366c0). The firmware on these chips can be patched using the nexmon-csi tool [17]. Firmware patching is required only for the Rx end as CSI on Rx is what we aim to collect. Commonly, WiFi manufacturers make sure that CSI data on the Routers is kept private for the internal usage only. Hence, firmware patching is

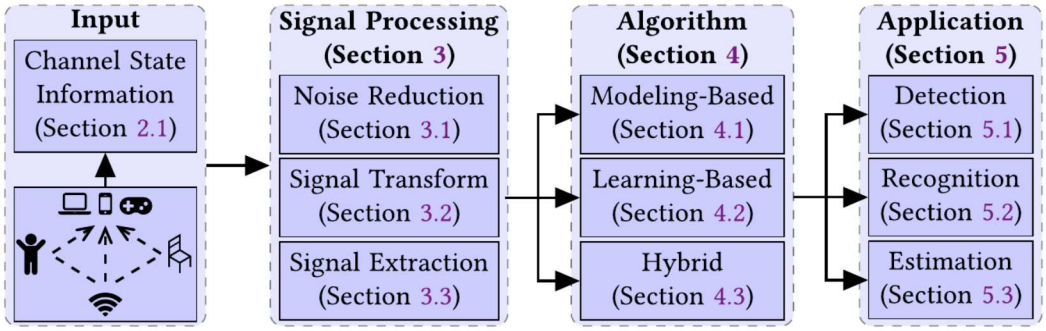

FIGURE 4.1: Flowchart of WiFi Sensing

another critical steps for this work as this enables us to get the access of protected CSI data.

Moreover, these routers have 3 external detachable antennas and one internal antenna. We have used external antennas to capture 1x1, 2x2 and 3x3 spatial streams. Importantly, these routers also have two USB ports 2.0 and 3.0, that serve as a helpful resource to store the data being collected externally.

For collecting the data we have kept these routers at a distance of 0.5 meters with plywood walls (with different MC levels) centered in-between. We are capturing Line-of-Sight (LOS) data in this case with RF waves going from Tx to Rx and having a wall in between. The top and side views of the setup are demonstrated in figures 4.3 and 4.2 respectively.

Further, the plywood pieces that we have used as a wall structure are of size 2x2 sq. ft. A moisture meter is being used to measure MC of these different plywood walls and depending on the average of 4 readings at different locations the label to collected CSI is given. To elaborate, if the MC level is greater than 15% on moisture meter then we label it as unsafe and if the MC level is lower than 15% we label the data as safe. Figures 4.4 and 4.5 depict two of these plywood MC levels.

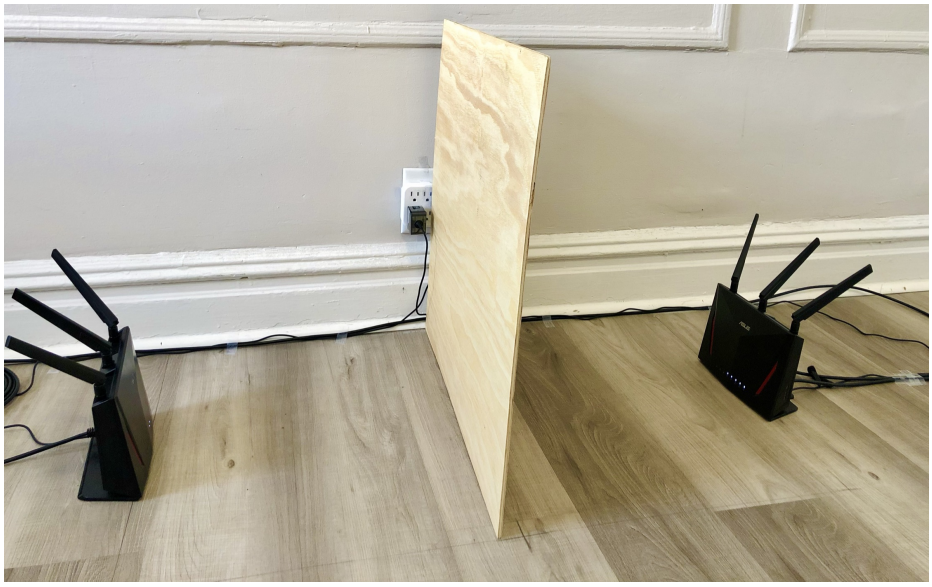

FIGURE 4.2: Physical Setup - Side View

FIGURE 4.3: Physical Setup - Top View

4.2 Nexmon tool

The whole process of collecting CSI dataset for different channel bandwidths was enabled because of the open-source Nexmon-CSI tool [16] [17]. This project allows you to extract CSI of OFDM-modulated Wi-Fi frames (802.11a/(g)/n/ac)

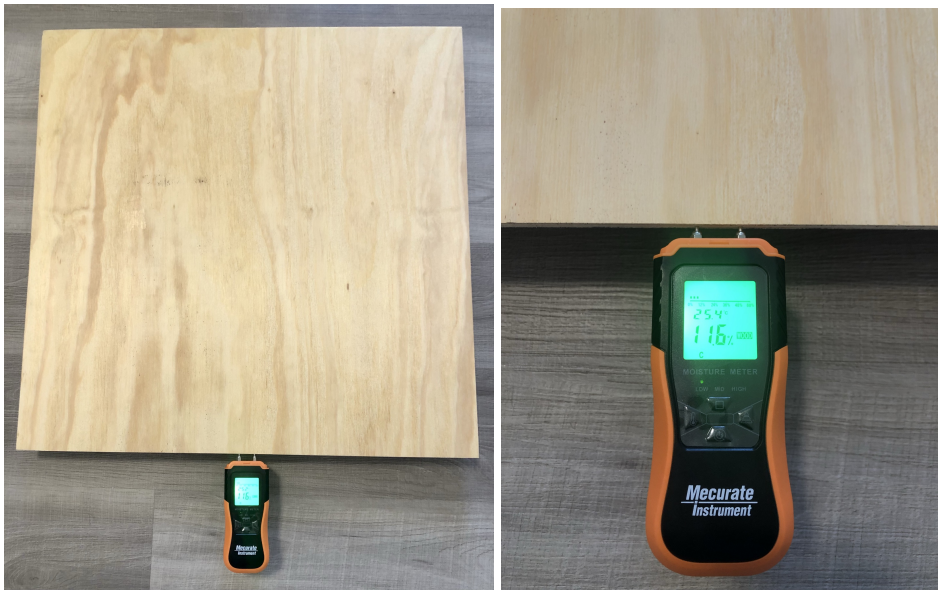

FIGURE 4.4: Plywood wall with safe MC levels = 11.6%

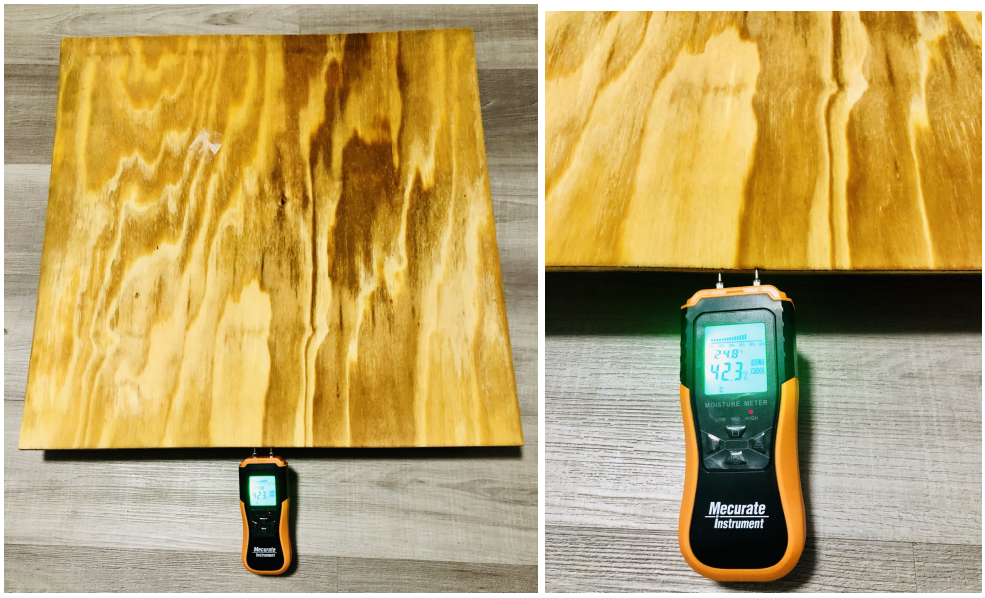

FIGURE 4.5: Plywood wall with unsafe MC levels = 42.3%

Tool	Open Source	Device	Supp. Chipset	max. BW	NSS×NRX	Supp. Std.	NSC	Res.
nexmon CSI Extractor	yes	Router, PCIE e.g. Asus RT-AC86U	BCM43{65, 66}	80 MHz	4×4	VHT/11ac	242	12 bit (f)
	yes	Smartphone, IoT e.g. Nexus 5/6P, RPi3B+/4B	BCM43{39, 58, 455}	80 MHz	1×1	VHT/11ac	242	14 bit (i) or 10 bit (f)
Linux 802.11n CSI Tool	no	PCI	IWL5300	40MHz	3x3	HT/11n	30	8 bits (i)
Atheros CSI Tool	yes	Router, PCIE	AR9580, AR9590 AR9344, QCA9558	40MHz	3x3	HT/11n	114	10 bits (i)
OpenFWWF CSI Tool	no	Router, PCI e.g. Linksys WRT54GL	BCM4318	20MHz	1x1	OFDM/11g	52	12 bits (i)

FIGURE 4.6: Trade-off between popular CSI collection tools.

on a per frame basis with up to 80 MHz bandwidth on the Broadcom Wi-Fi Chips.

There are some other tools available for the same purpose and their trade-offs are listed in figure 4.6. However, it works on a diverse range of devices including Raspberry Pi. The maximum number of sub-carriers accessible through this tool are 242 with a 12-bit complex double representing each CSI data member. Furthermore, Nexmon-CSI is the most versatile of them all as it provides free firmware patching software tools to enable CSI extraction, programs to configure the extractor, enable monitor mode and then to collect CSI by listening on UDP socket 5500. In the next subsection we have analyzed the composition of a single packet captured using Nexmon-CSI tool.

4.2.1 Frame Composition

There will be one UDP packet per configured core and spatial stream for each incoming frame (1 Kb each) matching the configured filter. Each UDP packet containing collected CSI has 10.10.10.10 as source address and is destined to 255.255.255.255 on port 5500. Frame structure from the first byte to last is given below:

- The payload = four magic bytes 0x11111111.

- This is followed by a 6 byte source mac address.
- Followed by a 2 byte frame sequence number
- Followed by 2 bytes contain core and spatial stream number (bitwise)
- Followed by 2 bytes for channel specification
- Followed by 2 bytes for chip version.
- Finally, actual CSI data follows till the end of the packet.

In the bcm4366c0 broadcom chips, relative to using 20, 40, or 80 MHz wide channels which are 64, 128, or 256 times four bytes long. The data contains interleaved int16 real and int16 imaginary parts for each complex CSI value.

ASUS Routers return values in a floating point format with one bit sign of the following nine or twelve bits of a real part and the same for an imaginary part, followed by an exponent of five or six bits.

4.3 Dataset Creation

4.3.1 Data Collection

Collecting the dataset is an important step in the process of building a classification pipeline. The main goal in this step is to maximize the collection of learnable features. While collecting the CSI data, special care needs to be taken as the CSI is affected by even minute changes in the surroundings.

To save the data tcpdump is used to gathter CSI packets and save them to a flashdrive mounted on USB port of the Rx end router. tcpdump provides functionality to store a set number of packets and merge them into a .pcap file format. For our work, we have collected the CSI data at channel number 36. For each

bandwidth of 20MHz, 40MHz and 80MHz; 1x1, 2x2 and 3x3 Spatial Stream data is collected. We have collected 5000 packets from the plywood wall with safe MC levels and 5000 packets for plywood wall with unsafe MC levels. This is repeated for each channel bandwidth and all the SS resulting in 18 pcap files captured. These combinations of SS and bandwdth for safe and unsafe pcap files can be understood from the table 4.1. In this table, the dataset name ending with 'd' corresponds to safe MC levels dataset and the dataset label ending with 'w' corresponds to unsafe MC levels dataset.

TABLE 4.1: Collected Data Description for Channel 36 (*.pcap* files)

Bandwidth	1 SS	2 SS	3 SS	Size	Type
20 MHz	dataset1d	dataset2d	dataset3d	5000x64	complex double
40 MHz	dataset4d	dataset5d	dataset6d	5000x128	complex double
80 MHz	dataset7d	dataset8d	dataset9d	5000x256	complex double
20 MHz	dataset1w	dataset2w	dataset3w	5000x64	complex double
40 MHz	dataset4w	dataset5w	dataset6w	5000x128	complex double
80 MHz	dataset7w	dataset8w	dataset9w	5000x256	complex double

4.3.2 Data Processing

These pcap files are then processed in MATLAB to extract out complex numbered values for each sub-carrier from the hexadecimal data members in pcap

file. The size of matrices consisting of these complex valued member depends on the bandwidth for which pcap files were collected. As it can be seen on table 4.1, for 20MHz BW the size of complex-valued matrix is 5000x64, for 40MHz BW the size of complex-valued matrix is 5000x128 and for 80MHz BW the size of complex-valued matrix is 5000x256.

Later, we convert these matrices of complex-values pair to matrices of amplitudes of the CSI signals. This is done simply by calculating the absolute value out of real and imaginary parts of the complex number. This is done as the CSI-Net which we are using for our classification task takes in as inputs only the amplitudes of CSI signals.

The MATLAB code for data collection and processing can be found here.

4.3.3 Storing Datasets

Once the conversion is done, we merge the safe and unsafe datasets for a particular BW and SS resulting in a matrix of length 10000. From this matrix we split the dataset such that we get the training data of length 8000 with 4000 safe MC level data members and 4000 unsafe. Consequently. the test data of size 2000 also has equal proportions of safe and unsafe MC levels data members. training data, test data and corresponding labels are then saved into a .mat file using MATLAB.

We repeat this for all BWxSS pairs and get 9 datasets of size 10k with 8k training packets and 2000 testing packets. A full list of collected datasets can be seen on table 4.2.

TABLE 4.2: Dataset list (*.mat* Files) for channel 36 (5180MHz)

Name	Bandwidth	SS	training packets	test packets
dataset1	20 MHz	1	8,000	2000
dataset2	20 MHz	2	8,000	2000
dataset3	20 MHz	3	8,000	2000
dataset4	40 MHz	1	8,000	2000
dataset5	40 MHz	2	8,000	2000
dataset6	40 MHz	3	8,000	2000
dataset7	80 MHz	1	8,000	2000
dataset8	80 MHz	2	8,000	2000
dataset9	80 MHz	3	8,000	2000

4.4 Network Architecture

The network architecture that we have created is inspired from CSI-Net [6] which itself has a Resnet [5] backbone. CSI-Net has three constituent functional components:

1. **Generation Stage**
2. **Features Learning Stage**
3. **Task Stage**

In the Generation stage, the CSI data is transformed to feature maps with the spatially encoded patterns. These spatially encoded patterns are then mapped to features for the binary classification in the Feature Learning stage. Ultimately, outputs are produced as per these features in the Task stage. A symbolic view of the CSI-Net architecture is represented in the figure 4.7

4.4.1 Inputs to the Network

We have used three different input sizes for 3 different channel BW. Input size of the network was changed accordingly during the training, however, keeping

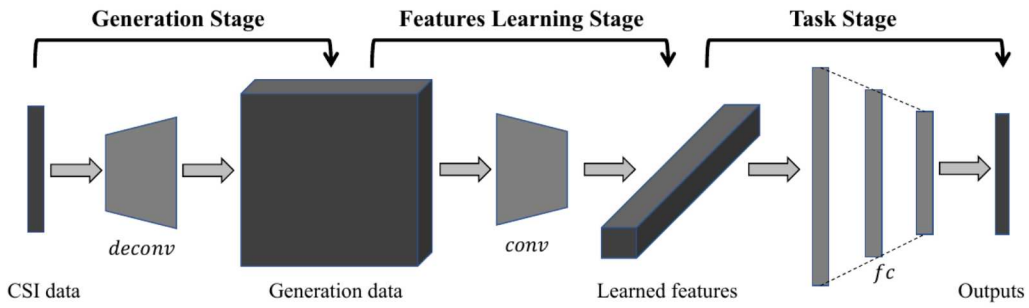

FIGURE 4.7: Architecture of CSI-Net.

the rest of the network intact. CSI data coming from the pcap files is a complex-valued sequence, $\mathbf{A} \in \mathbb{C}^{\mathbf{N_{sa} x N_{sc} N_{tx} N_{rx}}}$, where N_{sa} and N_{sc} are length of the sampled sequence and number of sub-carriers. Further, N_{tx} and N_{rx} are number of Tx and Rx antennas. For our datasets, for each time step we have following tensor size as input:

Channel BW : 20MHz $\rightarrow 64 \times 1 \times 1 \quad tensor$

$ChannelBW : 40MHz \rightarrow 128 \times 1 \times 1 \quad tensor$

$ChannelBW : 80MHz \rightarrow 256 \times 1 \times 1 \quad tensor$

4.4.2 Generation Stage

CSI-Net is built using transposed convolution (TC), also called deconvolution. The information inside a channel of the input tensor is exploited by the generation stage. We here mount 8 TC layers to take the 64x1 x1 input tensor, and produce a tensor of 6x224x224. The later the target tensor size is set of 224 x 224.

4.4.3 Feature Learning Stage

Feature learning stage takes the 6x224x224 tensor from the generation stage and extracts features for the final tasks. Following the generation stage, any computer vision based CNN can be used as a backbone. We have used a ResNet for

this part.

4.4.4 Task Stage

The task stage leverages above learned features to calculate the outputs for the task of binary classification. This stage has multiple fully-connected layers, activation function and loss function. We compute the loss for the classification as a Binary Cross-Entropy / Log Loss.

4.4.5 Training Networks

The Neural Network was implemented in Pytorch. It was trained on a Ubuntu machine with a NVIDIA GeForce RTX 2060 GPU. We train the networks with 20 MHz and 40 MHz BW datasets for 10 epochs with a mini-batch size of 20 and initial learning rate of 0.001. However, due to a larger size of 80MHz BW datasets, training was done for 10 epochs with a minibatch size of 4. For each BW the network was trained for 3 different SS datasets. Hence nine different networks were trained and network weights after training were store for future usage. The Optimizer used in all nine cases is Adam.

Chapter 5

Results

First key result this work has tried to achieve is a collection of valuable and diverse CSI dataset. Another key result of this work is a binary classifier that categorizes through-wall CSI data to predict structural strength of the wall to be safe or unsafe. Further details of these works are mentioned in the below sections.

5.1 Datasets

Primary dataset collection provides 9 datasets varying in number of spatial stream and channel bandwidth. The data members for in these are amplitudes of the RF signals for each subcarrier on channel 36. These datasets also have labels associated with them. label - '0' is for the CSI corresponding to safe MC levels in plywood wall. And, label - '1' refers to the unsafe levels.

Along with these primary datasets, we have also saved the dataset having CSI with complex values in pcap file format. Code is also provided through which these pcap files can be converted to .mat files containing complex-values CSI data.

Raw pcap data files with complex-valued CSI can be found here

Final datasets created with CSI subcarrier amplitudes can be found here.

5.2 Classification Efficiency for Different Datasets

This section compares our analytical results for different BW x Spatial Stream CSI data.

TABLE 5.1: Classification Accuracies for 20MHz Band

Dataset	Training Accuracy	Test Accuracy
dataset1	98.67	97.85
dataset2	97.412	93.9
dataset3	98.125	91.2

For the 20MHz bandwidth, highest test accuracy is achieved for dataset with 1x1 spatial stream. Test accuracy reduces for 2x2 spacial stream data and is least for the 3x3 spatial stream data. However, this least accuracy is also over 90% indicating that the classifier would correctly predict the state of plywood wall almost 9 times out of 10 attempts. Classification accuracy for these datasets are tabulated in table 5.1

TABLE 5.2: Classification Accuracies for 40MHz Band

Dataset	Training Accuracy	Test Accuracy
dataset4	99.5	98.55
dataset5	98.225	90.15
dataset6	97.2	89.35

For the 40MHz classifiers, similar pattern is seen as in 20MHz classifiers. Test efficiency of 98.55% from single spatial stream data, is highest for any dataset collected and classifier trained in the whole collection of datasets. Further, test accuracy decreases with increasing spatial streams as seen in 20MHz results. A possible reasoning behind this is provided in the following subsection. 5.2.1

Results for the 80MHz channel bandwidth do not follow the same pattern as other two bandwidths. In this case the highest test accuracy is still achieved by the 1x1 spatial stream dataset. However, surprisingly, this efficiency is not

TABLE 5.3: Classification Accuracies for 80MHz Band

Dataset	Training Accuracy	Test Accuracy
dataset7	98.1	96.35
dataset8	96.57	86.65
dataset9	93.362	91.2

higher than the highest test efficiencies achieved by 20MHz and 40MHz bandwidth dataset. Further, the test accuracy attained for the 2x2 SS dataset for 80MHz bandwidth is lowest. This pattern is also not as it was expected to be. Both single spatial stream and 3x3 spatial stream classifiers gave an accuracy above 90%. Exact training and testing efficiencies can be referred in table 5.3

Network weights corresponding to these classification inaccuracies can be found here.

5.2.1 Reasoning

Possible reasoning for the pattern seen in these results is as follows:

As the received signal from surrounding may also be reflected off other objects in the environment then received by antennas, the system might be considering incorrect feature points for these reflected/scattered waves. This problem gets worse as number of spatial streams increase as now the system is collecting data from higher number of spatial stream instead of a single antenna pair. Hence, the accuracy of system decreases as number of spatial streams increase for the same bandwidth signal.

Chapter 6

Conclusions and Future Work

As part of this work we have created 9 rich datasets of CSI data varying in Bandwidth and Spatial streams for channel number 36. Further, We have created a binary classifier to categorize between safe and unsafe plywood wall to be used in construction purpose. We worked with multiple tools ranging from MATLAB to Nexmon-CSI and from tcpdump to Google Colab.

6.1 Conclusion

In this thesis, along with the details on implementation for creating a target classifier network, we have also provided code files for data collection, processing and storage. Below we have briefly mentioned key points from each chapter in this work as a part of closure.

Chapter 1 mentions the motivation behind creating a novel, simple and low cost method to perform MC level classification task.

In Chapter 2, we get a broad understanding of all the ongoing research involving RF signals for robot perception problems. Further, we listed some of the noteworthy works involving WiFi CSI usage to solve different problems and finally we discuss some methods similar to usage of WiFi CSI for MC level based classification.

In Chapter 3, great details are provided to support the reader with the math and physics required for understanding the whole process. Insightful knowledge pertaining to EM waves, WLAN and WiFi CSI is shared to prepare the reader for next set of chapters.

In Chapter 4, we dive deeper into the core of methodology we used to solve the classification problem. It illustrates the physical setup we created. Further, gives details about the router setup. It also provides specifics of using nexmon-csi tool and analysis of captured CSI packet. The complete pipeline from collecting packets to creating the dataset is shared. And at the end, details about the network architecture and training are shared.

6.2 Future Work

This field appears to be very lucrative from the research point-of-view. There are multiple suggestions and inclinations for further advancement of this work. The following extensions are planned for future work:

- Estimation of the quantitative MC.
- Creating insulation material MC levels classifier.
- Usage of both amplitude and phase difference to perform classification task.
- Usage of VGG [73], Inception [74], AlexNet [75] and comparison with ResNet based results.
- More categories may be added and a multi-class classifier can be created taking this work as a basis.

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