ENJOYING MOVIES DURING WORKOUT: GAIN OR LOSS?

PROJECT - PART 2 (CS570004) report submitted to

Indian Institute of Technology Kharagpur

in partial fulfilment for the award of the degree of

Master of Technology

in

Computer Science and Engineering

by

HARSH PRITAM SANAPALA

(17CS30016)

Under the supervision of

Professor Sandip Chakraborty

Computer Science and Engineering

Indian Institute of Technology Kharagpur

Spring Semester, 2021-22

April 25, 2022

DECLARATION

I certify that

(a) The work contained in this report has been done by me under the guidance of my supervisor.

(b) The work has not been submitted to any other Institute for any degree or diploma.

(c) I have conformed to the norms and guidelines given in the Ethical Code of Conduct of the Institute.

(d) Whenever I have used materials (data, theoretical analysis, figures, and text) from other sources, I have given due credit to them by citing them in the text of the thesis and giving their details in the references. Further, I have taken permission from the copyright owners of the sources, whenever necessary.

Date: April 25, 2022 (HARSH PRITAM SANAPALA)

Place: Kharagpur (17CS30016)

COMPUTER SCIENCE AND ENGINEERING
INDIAN INSTITUTE OF TECHNOLOGY KHARAGPUR
KHARAGPUR - 721302, INDIA

CERTIFICATE

This is to certify that the project report entitled "**ENJOYING MOVIES DURING WORKOUT: GAIN OR LOSS?**" submitted by **HARSH PRITAM SANAPALA** (Roll No. 17CS30016) to Indian Institute of Technology Kharagpur towards partial fulfilment of requirements for the award of degree of Master of Technology in Computer Science and Engineering is a record of bona fide work carried out by him under my supervision and guidance during Spring Semester, 2021-22.

Date: April 25, 2022
Place: Kharagpur

Professor Sandip Chakraborty
Computer Science and Engineering
Indian Institute of Technology Kharagpur
Kharagpur - 721302, India

Abstract

Name of the student: **HARSH PRITAM SANAPALA** Roll No: **17CS30016**

Degree for which submitted: **Master of Technology**

Department: **Computer Science and Engineering**

Thesis title: **ENJOYING MOVIES DURING WORKOUT: GAIN OR LOSS?**

Thesis supervisor: **Professor Sandip Chakraborty**

Month and year of thesis submission: **April 25, 2022**

In our increasingly wireless world, we have seen the growth of Wi-fi networks around us in a booming fashion, rightfully so because of the ease of installation and high throughput. There is a rapid growth in smart homes, smart or digital workplaces, and digital recreational and fitness centres. A particular use case in this regard is to monitor the health and fitness activities of gymnasium users. In the fast-growing developments made to fitness centres, one aspect is to incentivize fitness. One such incentive is to provide free video streaming services and organize watch-along for members. Gym goers use the video streaming experience to make their workouts more fun. As this is a growing use case, we try to analyze the effects of watching videos while working out simultaneously. Channel State Information (CSI) is becoming a ubiquitously used sensing tool. Previous works have thrown light on using CSI data to examine coarse-grained and fine-grained characteristics using amplitude and phase properties. We focus on treadmill workouts to narrow our vision to find any intriguing observations related to that. We try to leverage CSI data collected to analyze workout patterns on a treadmill while streaming videos. We use a fitness band along with an ESP32 to record the ground truth and CSI data, respectively. We try to apply signal processing techniques to the collected data and to some Stationary Data where the subject is idle to find any similarities in the amplitude and phase of the CSI data that could lead to utilizing CSI data as a tool for estimating workout trends.

Acknowledgements

I want to express heartfelt thanks to my supervisor Prof. Sandip Chakraborty for giving me the opportunity to work on Systems and Networks. Moreover, I would like to thank him for giving me the freedom and inspiration to encompass my ideas in the project.

I'm thankful to my Faculty Advisor, Dr Debasis Samanta, Associate Professor, Department of Computer Science and Engineering Department, IIT Kharagpur, for conducting various academic activities promptly. I would also like to thank the department for giving me the opportunity to work on this project.

I am sincerely grateful to my father, Dr S. Viziananda Row, who helped me with the data collection part of the project. I want to mention Transformers Gym, Visakhapatnam and ABS Fitness Gym, Visakhapatnam, the fitness centres which allowed me to conduct the experiments. I would also like to thank Srikanth and Jagadeesh, who volunteered for the initial part of the experiments.

I am grateful to my parents and friends, without whose love and guidance I would not have gotten this far.

Harsh Pritam Sanapala

Contents

Chapter 1

Introduction

1.1 Treadmill Workouts

Treadmills are fitness equipment generally used for exercises imitating walking or running. Usually, people use treadmills for cardio workouts, where raising the heart rate and maintaining it at a certain level is the target. These workouts expand their blood vessels to carry more oxygen, which in turn releases endorphins. The benefits of cardio exercises include preventing heart disease, improving mental health, and weight management. The Centers for Disease Control and Prevention (CDC) say there's extensive scientific evidence that 150 minutes of moderate-intensity cardio per week will help you maintain your weight over time. Another research has shown that getting your heart rate up with regular cardio exercises can help prevent cardiovascular disease, which accounted for 31 per cent of global deaths in 2012 [2]. Working out on a treadmill might become boring for some users due to the feeling of monotonous work. Since a treadmill is widely associated with cardio, manufacturers had to keep up with users' needs. In light of workout incentivization by gymnasiums and even by users themselves, gym equipment manufacturers like Peloton, NordicTrack came up with treadmills with screens attached for entertainment purposes.

Figure 1.1: NordicTrack Treadmill

The treadmills are equipped with Wi-fi and Bluetooth support for users to have a joyful workout of their choice. We try to understand the effects of having such equipment on their natural workout trends. We can monitor and provide the users with a healthier and entertaining exercise session of their liking. We can analyze any effects that pairing video streaming with exercises has on their fitness targets. And we can develop an optimal framework to tackle the same without fully curbing their paired activity.

1.2 Video Streaming

Since the rise of Content Delivery Networks (CDN), video streaming has become smoother and deftly available across the globe. Streaming services like Netflix, Amazon PrimeVideo, Disney+, Hulu, AppleTV+ have become significant players in the market. The competition amongst them has given rise to absorbing content that subscribers are consuming daily. With treadmills offering the capacity to deliver the services, the number of treadmill and video streaming users is growing. This rise in popularity leads to a thought - Whether watching a favourite show while exercising affects workout trends or statistics? This thought led to the following work.

1.3 Motivation

Channel State Information gives us detailed knowledge of a wireless link. It describes the current state or condition of a channel. We can infer some characteristics from the CSI data since it contains the attenuation and phase shift details experienced by a spatial signal stream from the transmitter to the receiver. Channel State Information is a valuable tool for sensing or even gesture recognition, for that matter. While going through several works related to Channel State Information, the idea of analyzing statistics of incentivized fitness paired with video streaming seemed an interesting one. Because of the extensive use of fitness equipment in today's world, the use case seemed ubiquitous. For analyzing workout patterns, CSI data could be a helpful mechanism to develop a framework to identify and understand if video streaming hurts workout trends and thereby notify users about the same. Therefore, it led us to explore a Digital Well-Being aspect of incentivized fitness.

1.4 Brief Idea about the Work Done

To understand the working of an ESP32 and the CSI tool that we employed, we started by exploring the CSI tool's sub-projects. These experiments helped us understand the process of CSI data collection and gave us an idea of how to make the best use of it. After we thoroughly understood the CSI tool and the working of an ESP32, we collected data related to our actual target use case, i.e. CSI data during treadmill workouts. After collecting the initial set of data, we could observe that there might be slight downtrends while streaming videos during an exercise. To utilize CSI data for estimating workout trends, we try to employ some signal processing techniques to filter out some noise and analyse only the critical parts of the CSI data.

1.5 Organization of the Report

The rest of the report is organized as follows. Chapter 2 talks about the background and related works in this field. Chapter 3 talks about the kind of experiments we did to understand Channel State Information. Chapter 4 talks about the data collection and analysis of the collected data with reference to the use case mentioned. We detail the signal processing techniques applied on the collected data and Stationary Data in Chapter 5. We provide the conclusion and talk about the scope of further work in Chapter 6.

Chapter 2

Background and Related Works

2.1 Channel State Information (CSI)

This information details how a signal propagates from the transmitter to the receiver. Typically, this information pertains to any known channel properties of a network communication link. It represents the combined effect of, for example, scattering, fading, and power decay with distance. Many works and researches have made it clear that CSI data is a valuable piece of information. Human activity recognition is possible by using CSI as a WI-fi sensing tool. Even though Wi-fi deployment techniques change with time, works related to CSI as a Wi-fi sensing tool shows promise.

2.2 ESP32

ESP32 is a system on a chip microcontroller with integrated Wi-fi and Bluetooth functionalities. It can act as an external network interface controller to a computer. Thereby, it allows us to extract CSI data over a communication link, either as a transmitter or as a receiver. This series of microcontrollers use low power and are

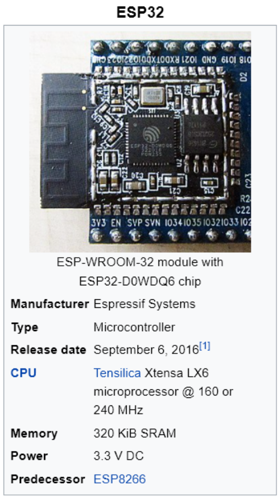

FIGURE 2.1: ESP32 Details

of low cost. Espressif Systems created and developed this series of chips. Espressif's IoT development framework ESP-IDF helps researchers to use programming languages like C and C++ for generic application development of their needs. Its open-source nature makes it easier for developers to work together to build exciting applications based on ESP32.

2.3 CSI tool

There are a few open-source CSI tools that are available to capture CSI data from a communication link. Researchers have developed each one of them with a particular series of chips in mind. For example, the Linux 802.11n CSI tool [5] is built on the Intel Wi-fi Wireless Link 5300 802.11n MIMO radios using custom modified firmware and open-source Linux wireless drivers. In our work, since we have concentrated on utilizing an ESP32, we use an ESP32 CSI toolkit developed by Steven M. Hernandez [6]. The ESP32 CSI toolkit collects CSI data from a Wi-fi enabled ESP32 controller. There are three projects included in this toolkit, and every one of them sends CSI data via a serial port in a CSV format. Upon collecting this data, researchers can apply their techniques with minimum additional effort.

2.4 Amplitude and Phase Characteristics

In ESP32, CSI information consists of channel frequency responses of sub-carriers. It is estimated when the transmitter receives the packets. Each channel frequency response of the sub-carrier - as two bytes of signed characters. The first one is the Imaginary part, and the second one is the Real part. According to the type of received packet, there are up to three fields of channel frequency responses. They are legacy long training field (LLTF), high throughput LTF (HT-LTF) and space-time block code HT-LTF (STBC-HT-LTF). For different types of packets which are received on channels with different state, the sub-carrier index and total bytes of signed characters of CSI is shown in the following table [1].

channel	secondary channel	none			below					above			
packet information	signal mode	non HT	HT		non HT	HT				non HT	HT		
	channel bandwidth	20 MHz	20 MHz		20 MHz	20 MHz		40 MHz		20 MHz	20 MHz		40 MHz
	STBC	non STBC	non STBC	STBC	non STBC	non STBC	STBC	non STBC	STBC	non STBC	non STBC	STBC	non STBC
sub-carrier index	LLTF	0~31, -32~-1	0~31, -32~-1	0~31, -32~-1	0~63	0~63	0~63	0~63	0~63	-64~-1	-64~-1	-64~-1	-64~-1
	HT-LTF	•	0~31, -32~-1	0~31, -32~-1	•	0~63	0~62	0~63, -64~-1	0~60, -60~-1	•	-64~-1	-62~-1	0~63, -64~-1
	STBC-HT-LTF	•	•	0~31, -32~-1	•	•	0~62	•	0~60, -60~-1	•	•	-62~-1	•
total bytes		128	256	384	128	256	380	384	612	128	256	376	384

FIGURE 2.2: ESP32 Wi-Fi CSI Info

We have 64 subcarriers corresponding to LLTF and 128 subcarriers corresponding to HT-LTF, and the CSI data received from ESP32 contains 128(only LLTF) or 256(only HT-LTF) or 384(LLTF and HT-LTF) values depending on the configuration set up in the CSI collection tool's menu. In the values we receive from the

ESP32, the Odd ones are the Real part, and the Even ones are the Imaginary part. We can then calculate amplitude and phase of i^{th} sub carrier as follows.

$$Amplitude_i = \sqrt{Real_i^2 + Imaginary_i^2} \tag{2.1}$$

$$Phase_i = \arctan(Imaginary_i, Real_i) \tag{2.2}$$

Previous works proved that amplitude distinguishes between coarse-grained characteristics, and phase shift distinguishes between fine-grained details.

2.5 Signal Processing Techniques

While handling the collected CSI data, we can observe a fair amount of noise and some outliers picked at random intervals by the CSI tool. Although we try to handle the outliers in the data preprocessing by omitting the problematic data points, we try to make sure that we do not have any more garbage or abnormal data points by employing signal processing techniques. These techniques help us understand the intricate details of the CSI data. By eliminating any potential noise, we will be able to pick up the critical data from the output of this signal processing. We normalize the data at first and then use a low pass filter to filter out higher frequencies. We use a Hampel filter for outlier removal, where the filter uses a sliding window and computes the median to estimate the standard deviation of that particular window. The filter then identifies points which lie at a distance greater than three times the standard deviation from the median and replaces that point with the window's computed median. For denoising the data, we try to use a Discrete Wavelet Transform on the obtained signal.

2.6 Related works

CSI as a sensing tool is a widely growing topic because of the amount of scope in it. There are a lot of ongoing works related to capturing CSI data to employ ingenious signal processing techniques to analyze and construct solutions to particular problems or use cases. LATTE [10] is a novel framework that proposes MU-MIMO group selection optimization for multi-user video streaming developed by Hannaneh Barahouei Pasandi and Tamer Nadeem. In LATTE, the researchers used CSI to track the motion of individual users. This data acts as an input to the RL agent that they designed. In the paper titled "Scalable Panoramic Wireless Video Streaming Relying on Optimal-Rate FEC-Coded Adaptive QAM" by Zhang et al. [15], they have found out that majority of the contributions on Unequal Error Protection (UEP) aided video streaming exploited CSI knowledge. Lee et al. [8] worked on "The Effects of Housing Environments on the Performance of Activity-Recognition Systems Using Wi-fi Channel State Information: An Exploratory Study", in which they studied monitoring systems that exploited CSI for activity recognition. Crepaldi et al. [4] worked on "Estimating Wireless Channel State Using CSI Sampling & Fusion", where they predict CSI of multi-stream settings using CSI obtained only from single-stream packets. Finger Pass [7] is a "Finger Gesture-based Continuous User Authentication for Smart Homes Using Commodity Wi-fi". Hao Kong et al. investigated Channel State Information of Wi-fi signals to find out that the CSI phase can distinguish unique behavioural characteristics. Meera Radhakrishnan, Archan Misra, and Rajesh Krishna Balan [12] proposed W8-Scope: Fine-Grained, Practical Monitoring of Weight Stack-based Exercises. Fine-grained, unobtrusive monitoring of gym exercises can help users track their exercise routines and provide corrective feedback. Yang et al. proposed a A Framework for Human Activity Recognition Based on WiFi CSI Signal Enhancement [14]. Heba et al. [3] proposed "A Ubiquitous WiFi-Based Fine-Grained Gesture Recognition System" - WiGest. They presented WiGest: a system that leverages changes in WiFi signal strength to sense in-air hand gestures around the user's mobile device. Yongsen et al. [9] worked on a survey about Wi-fi sensing with Channel State Information. This survey presented various techniques being employed in the ongoing research on CSI. Xuyu Wang et al. [13] worked on vital sign monitoring using CSI data. These are a few research works that served as inspiration for the following study.

Chapter 3

Exploring ESP32 for CSI Analysis

After going through a myriad of research papers regarding CSI, the best way to get a feel of it was to do some hands-on experiments. I experimented with the ESP32 that my guide has sent. I made use of the ESP CSI tool mentioned before to extract CSI data from the ESP32. Some experiments included graphing out the amplitude and phase characteristics of different gestures (inspiration from Finger Pass [7]). CSI data from the ESP32 comes out through the serial bus as a CSV file.

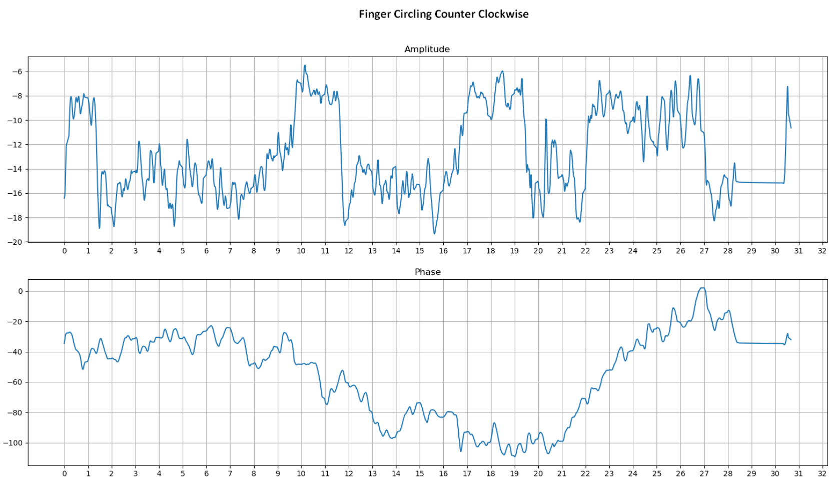

FIGURE 3.1: Finger Circling Counterclockwise

The shown graphs are a result of generating plots using the equations mentioned above for amplitude and phase. We can see from the amplitude plots that we can distinguish different gestures, which are coarse-grained features. These results corroborated the fact that CSI could be a powerful sensing tool. Some further experiments with ESP32 and the CSI tool led to the conclusion that we can obtain sufficient data points to pair the idea of CSI as a sensing tool with something else.

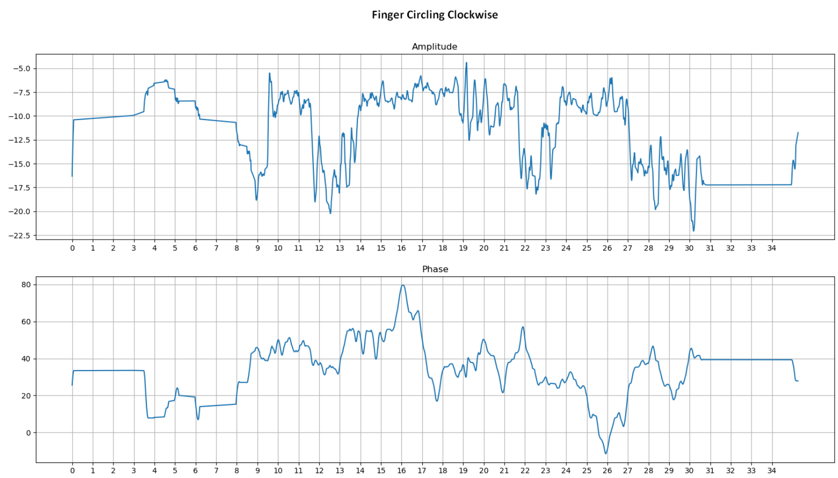

Figure 3.2: Finger Circling Clockwise

Chapter 4

Data Collection using ESP32

4.1 Experimental Setup

The idea is to collect CSI data and workout trends of treadmill users while streaming videos simultaneously to develop a framework that would benefit the overall digital well being of users. Although this is an initial point of view, we are open to using the data collected differently later if possible. For this particular flow, we need an ESP32, a fitness band, a laptop running Linux. Accordingly, my guide has provided me with the required ESP32, and I have got hold of a MiBand 6 fitness band to measure workout details.

Figure 4.1: Outline of Setup

By using the Active AP project of the ESP CSI tool, the ESP32 acts as an access point. Hence, it helps us establish a receiver at the ESP32's end. We can connect a mobile phone or another laptop to this gateway. After establishing a connection to the ESP32, the mobile phone can ping the gateway at regular intervals. We achieved this by using the IP tools application from Google Playstore. We have designed the transmitter-receiver network in this method. Once the setup design was complete, we had to visit a gymnasium to record initial data.

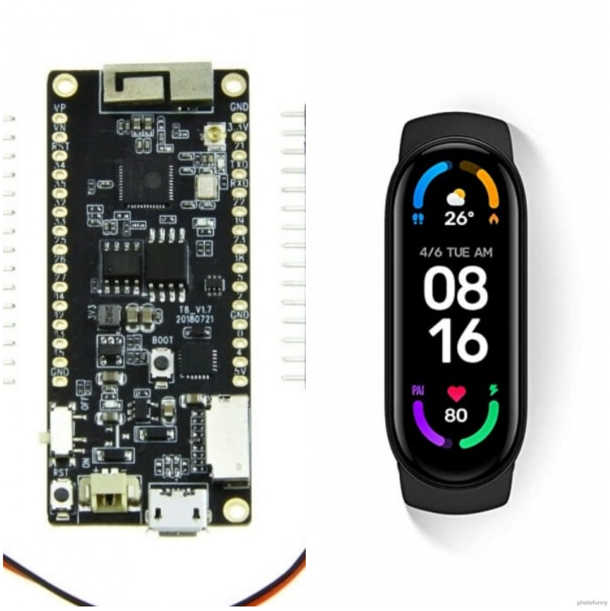

FIGURE 4.2: ESP32 and MiBand that were used

4.2 Data Collection

The first step was to connect the ESP to the laptop to collect data through the Serial bus. Then we flash the ESP CSI tool's Active AP project onto the ESP32 to make it work as an Access Point. We ask a volunteer to wear the fitness band and use the treadmill. Figure 4.3 shows the transmitter on the left end, which is a mobile connected to the ESP32 on the right end. The ESP32 as mentioned acts as a receiver.

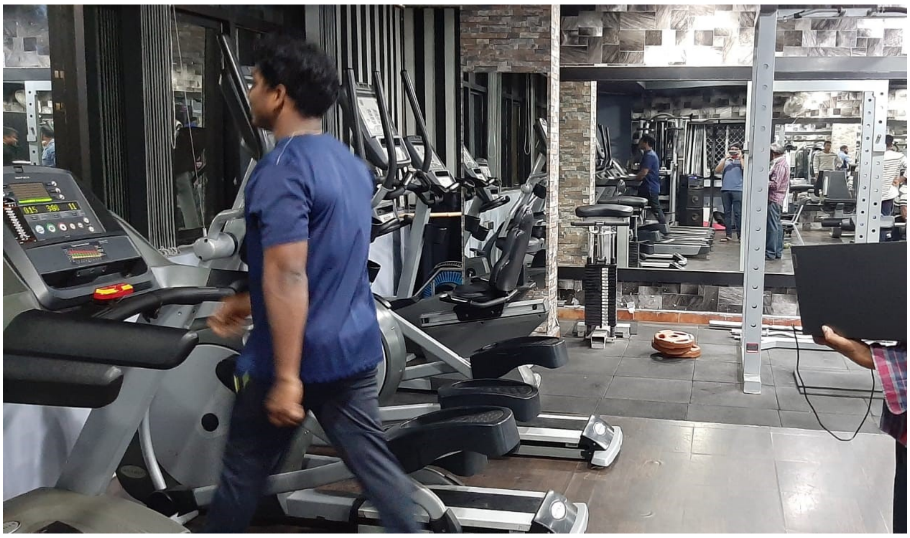

Figure 4.3: Experimental Setup at Gym

There are two parts to this experiment. First, we collect data when the subject is free from any distraction. We place the transmitter (an Android mobile) in front of the treadmill and ping the ESP32. We collect data for around four minutes approximately. Then, we repeat the process, but now we place another mobile in front of the subject to make him watch a YouTube video. The video chosen was an action sequence from the movie Transformers to make the subject as engaged as possible. And we collect the data for the duration of the video. We can infer and understand the setup and other details from the following pictures taken while collecting the data.

Figure 4.4: Data collection part 1 - no distraction

FIGURE 4.5: Data collection part 2 - Subject streaming a YouTube video

We collected data from another subject as well, but in another gymnasium to see if there may be any discrepancies. We followed the exact same procedure mentioned above for Subject number 2 as well.

FIGURE 4.6: Data collection on Subject 2 in a different Gym

4.3 Initial Analysis

4.3.1 Subject 1

From the data below, we can see that the workout trends have dipped a bit. The maximum and average heart rate values have dropped while watching a video. Also, the total calories burnt is surprisingly the same value even though the workout duration while watching a video was higher than the distraction-free workout. The heart rate graphs have also been presented as recorded by the MiFit application.

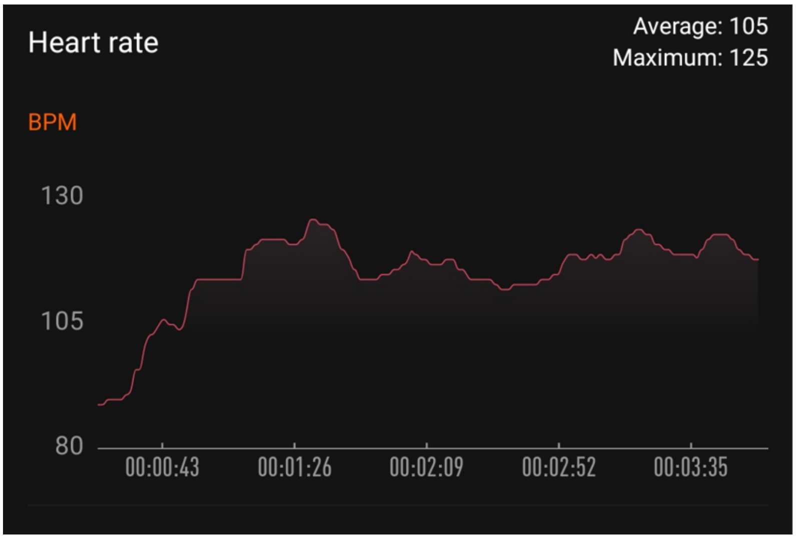

FIGURE 4.7: Heart Rate Graph during first phase of Subject 1 (no distraction)

Even though the workouts were light in nature, we can see that the distance recorded when using the treadmill without any distraction is higher for a shorter duration compared to watching a video and using the treadmill. This also explains the equal amount of calories burned even though time spent on the treadmill without any distraction is lesser.

Experiment	Time(s)	distance(steps)	avgPace	calories
No Distraction	215	450	0.74	23
Watching Video	307	440	0.878	23

TABLE 4.1: Workout trends.

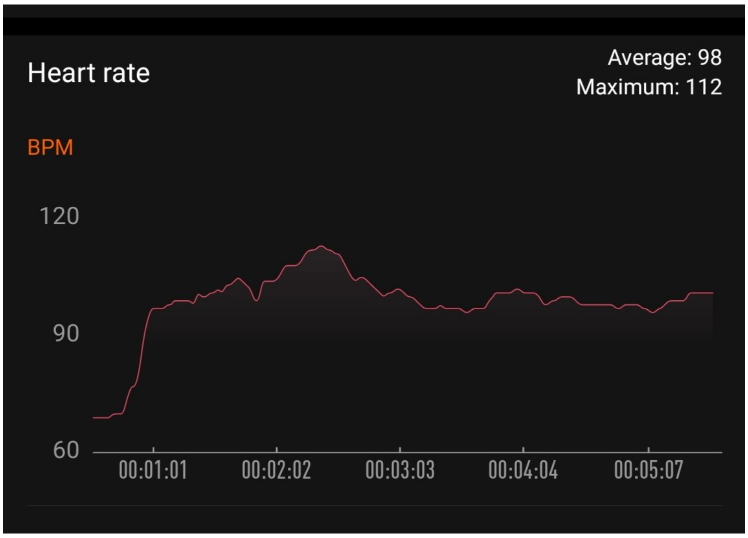

Figure 4.8: Heart Rate Graph during second phase of Subject 1 (watching video)

4.3.2 Subject 2

From the heart rate graphs below, we can see that the average heart rate for the distraction free phase is higher than the average heart rate recorded for the watching movie phase. We can also observe that the maximum heart rate recorded for the watching movie phase is slightly higher than for the distraction free phase. Since cardio workouts are about maintaining a higher heart rate throughout the workout, we do not have to view this as a discrepancy.

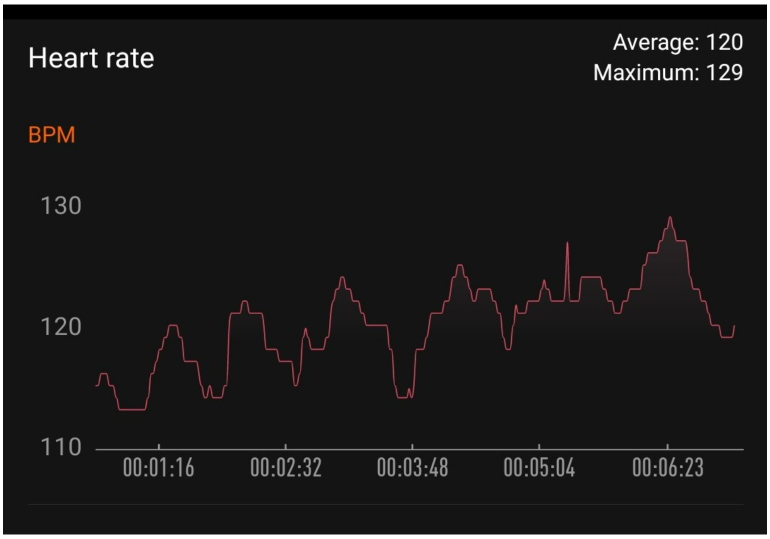

Figure 4.9: Heart Rate Graph during first phase of Subject 2 (distraction free)

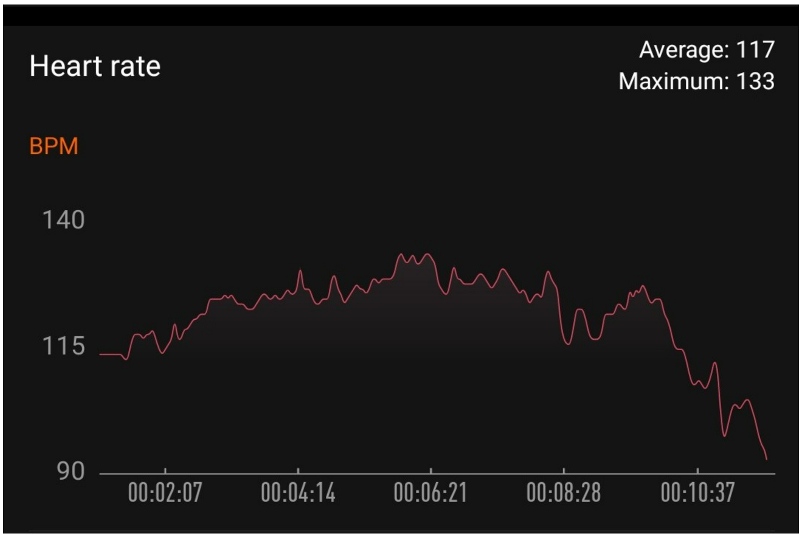

FIGURE 4.10: Heart Rate Graph during second phase of Subject 2 (watching video)

We try to correlate what we found from this ground truth with the CSI data that was collected and try to employ signal processing in the next step.

Chapter 5

CSI Analysis

5.1 Comparison of Raw CSI Data

The raw CSI data that we collected from the two subjects helps us understand the response of different subcarriers. When we plot the amplitude and phase responses without prior signal processing, we observe that in the LLTF subcarriers, Subcarriers 27-37 show no response at all, and the other subcarriers show more or less a similar response.

5.1.1 Distraction Free vs Watching Movie

For each LLTF subcarrier, we obtain amplitude and phase responses, and we plot the Distraction Free vs Watching Movie responses on the same plot to observe any conspicuous differences. As we can see from the plots, apart from some minor differences, we are not able to perceive any visible differences between Distraction Free vs Watching Movie plots. This leads us to use signal processing techniques to block out some signals and concentrate on certain frequencies only. Selected subcarriers have been represented in this report to avoid excessive data dump. All the data and plots can be found in this OneDrive Link [11].

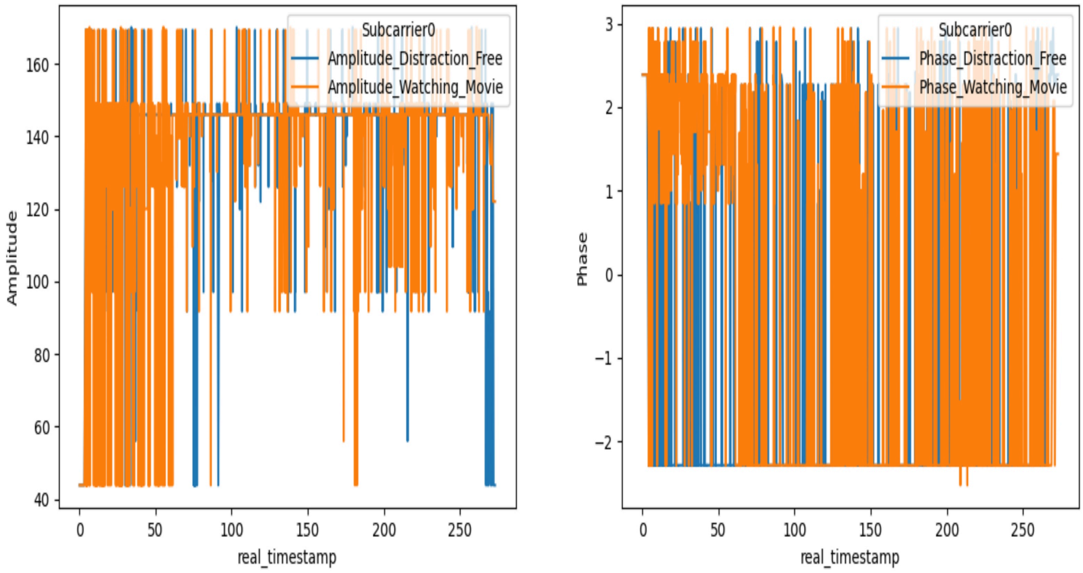

FIGURE 5.1: Subject 1 Subcarrier 1 Amplitude and Phase responses

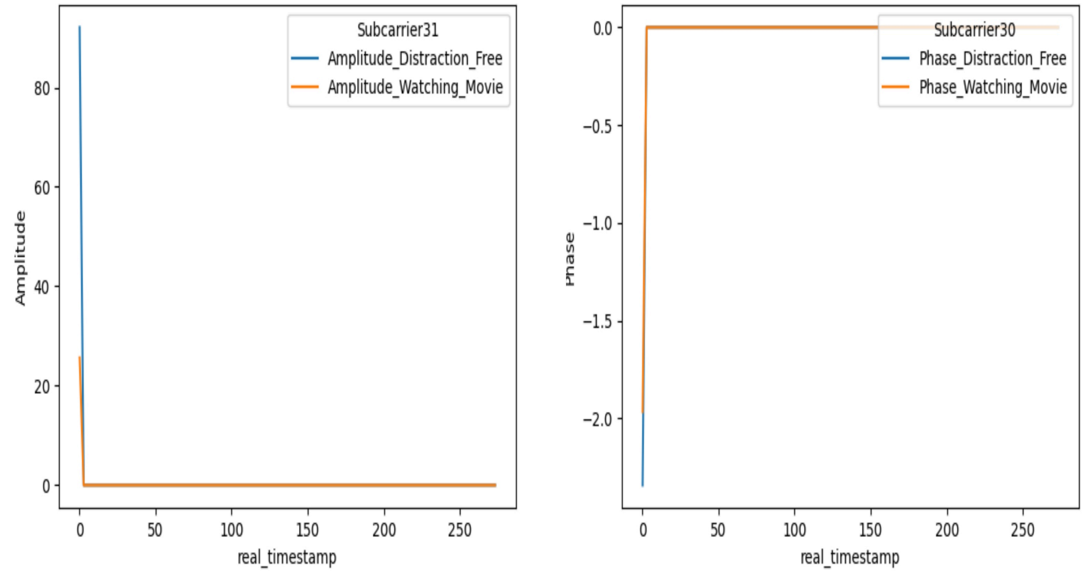

FIGURE 5.2: Subject 1 Subcarrier 32 Amplitude and Phase response

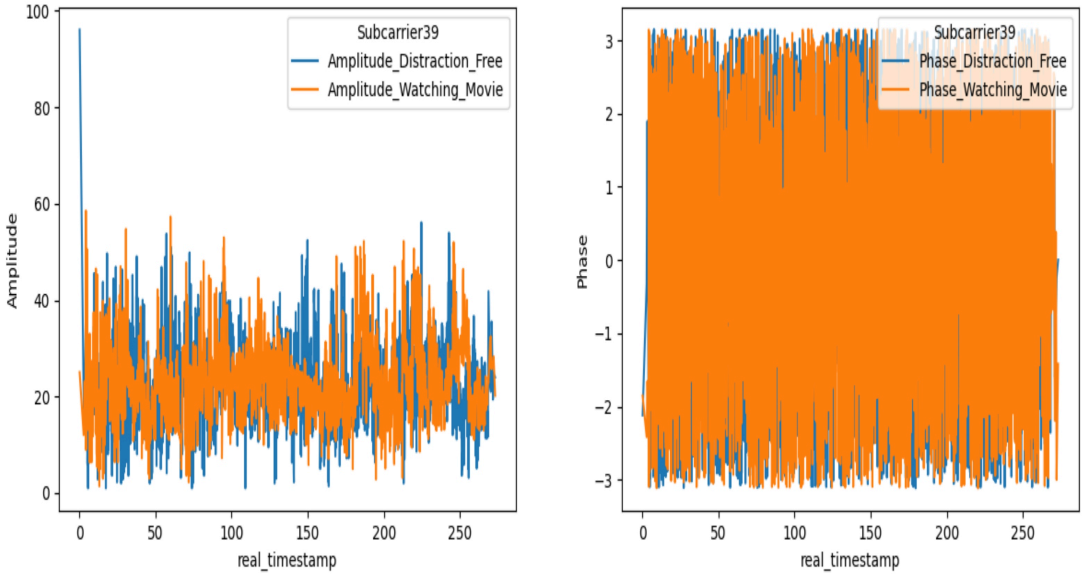

Figure 5.3: Subject 1 Subcarrier 40 Amplitude and Phase response

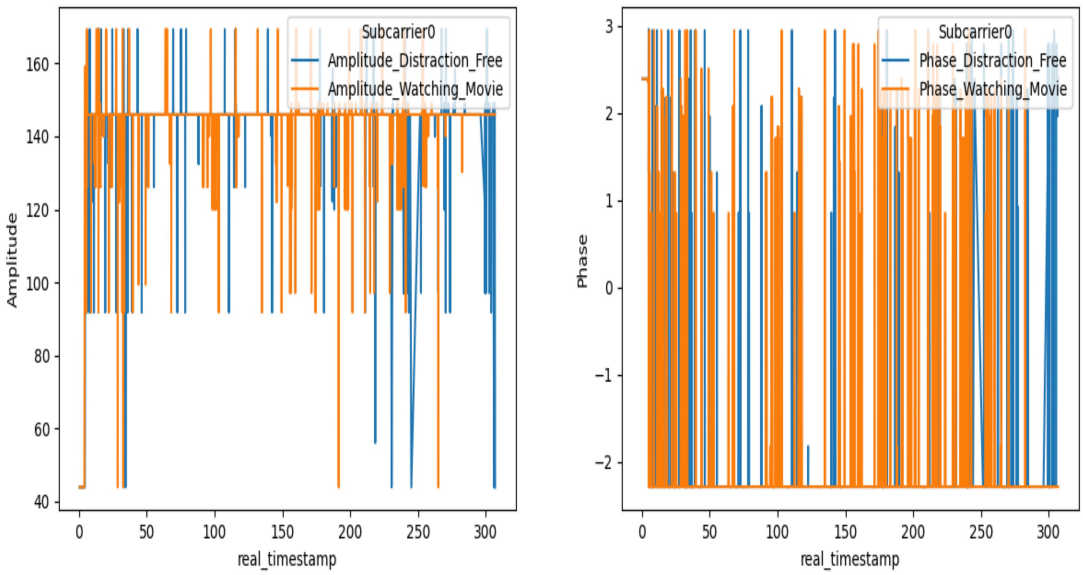

Figure 5.4: Subject 2 Subcarrier 1 Amplitude and Phase response

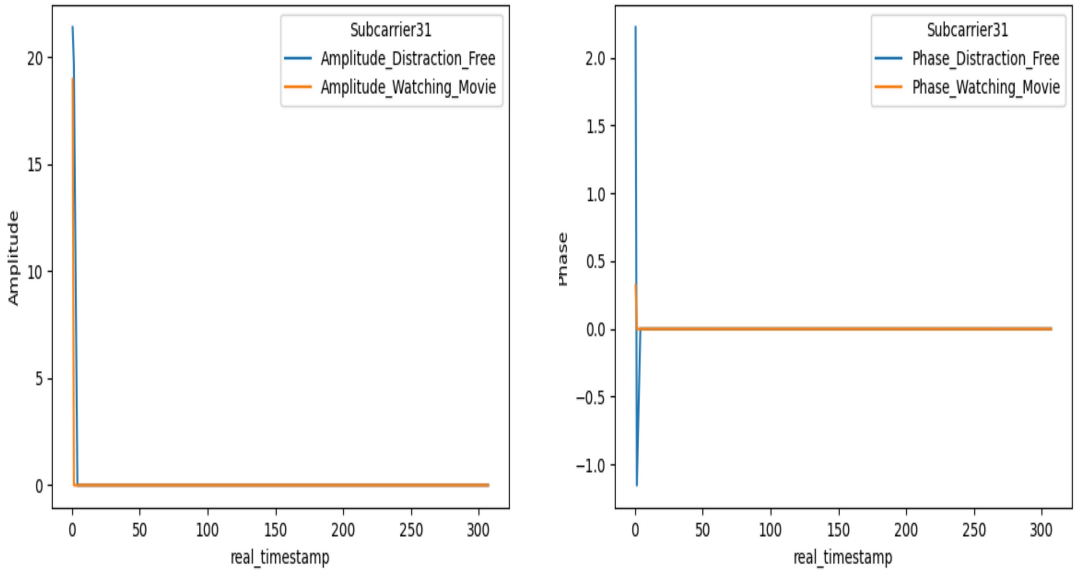

FIGURE 5.5: Subject 2 Subcarrier 32 Amplitude and Phase response

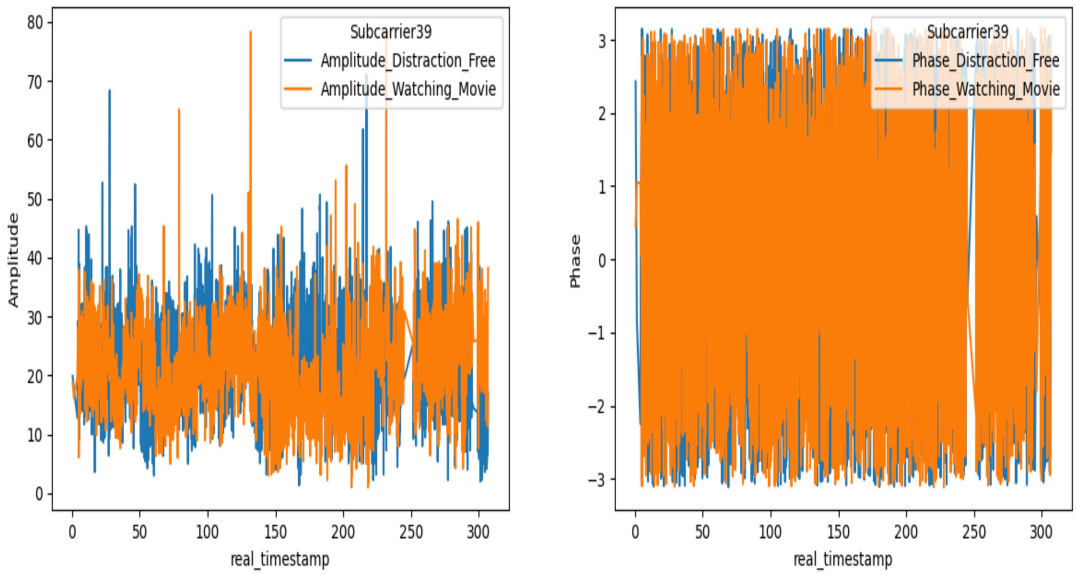

FIGURE 5.6: Subject 2 Subcarrier 40 Amplitude and Phase response

5.2 Stationary Data

To proceed with our investigations, we went through the PhaseBeat research paper, where the authors tried to monitor vital signs using CSI data. Taking inspiration from their work, we wanted to employ signal processing techniques on the data we collected and on some Stationary Data. Stationary Data is the data we collect when the subject is idly sitting in the same experimental setup that we used before. This data might provide some information if compared with the data we obtained from our initial experiments.

5.3 Signal Processing

We start by experimenting with the Stationary Data collected. Firstly, we normalize the amplitude and phase values. While collecting the Stationary Data, we made sure that we obtained different sampling rates to see if they would lead us somewhere. To normalize the data, we use a simple Min-Max normalization technique. Once we obtain the normalized data frames, we employ a smoothening pipeline consisting of a Low Pass Butterworth Filter and a Savitzky–Golay filter. Savgol filter tries to improve precision without meddling with the signal tendency. We then use a Hampel filter for replacing any outliers at a distance greater than three times the standard deviation from the median of the current window, with the median. To denoise further, we use Discrete Wavelet Transform on the resulting data. The results of the signal processing can be seen in the following plots. We compare the results of Stationary Data with Subject 1's Distraction-Free and Watching Movie data.

5.3.1 Stationary Data Plots

To avoid clumsiness, we focus on a single subcarrier in this report. The plots name the subcarriers from 0, so Sub39 is same as 40^{th} subcarrier. All the plots can be found in the mentioned OneDrive link[11].

We can see that some subcarriers show no response from the compressed plots.

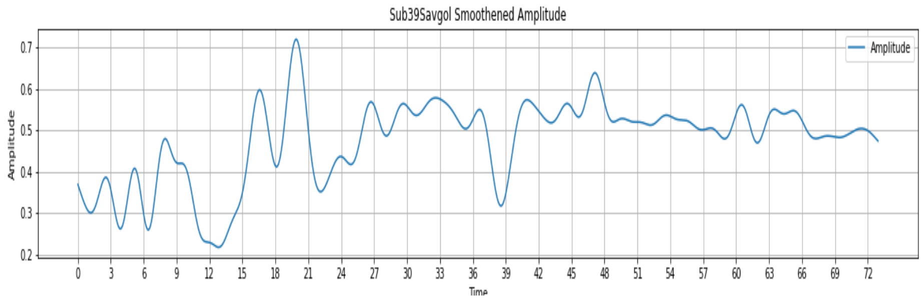

FIGURE 5.7: Stationary Data Subcarrier 40 Amplitude after smoothening with Savgol Filter

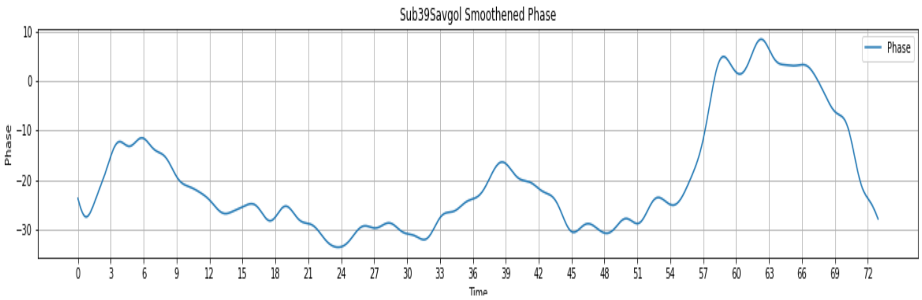

FIGURE 5.8: Stationary Data Subcarrier 40 Phase after smoothening with Savgol Filter

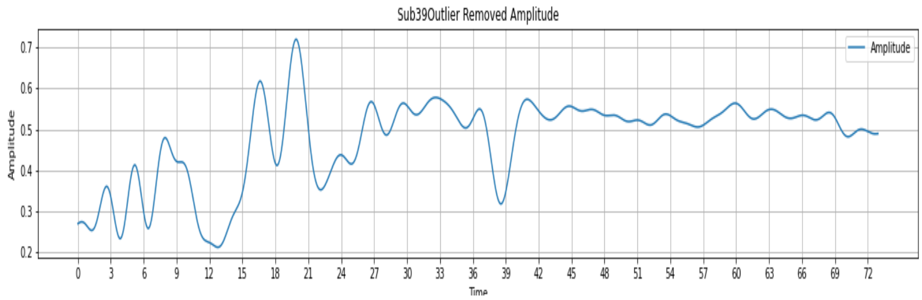

FIGURE 5.9: Stationary Data Subcarrier 40 Amplitude after Outlier Removal with Hampel Filter

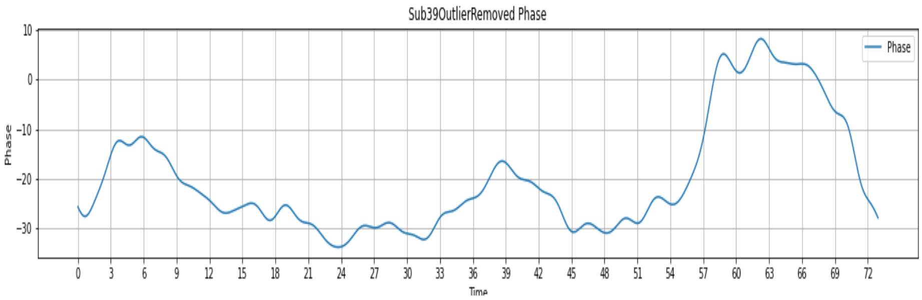

FIGURE 5.10: Stationary Data Subcarrier 40 Phase after Outlier Removal with Hampel Filter

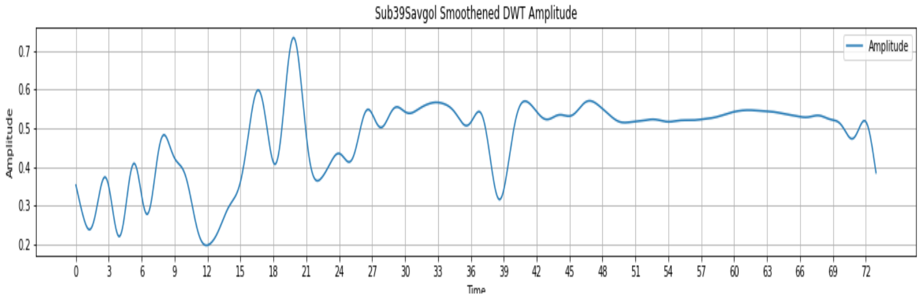

FIGURE 5.11: Stationary Data Subcarrier 40 Amplitude after denoising with DWT

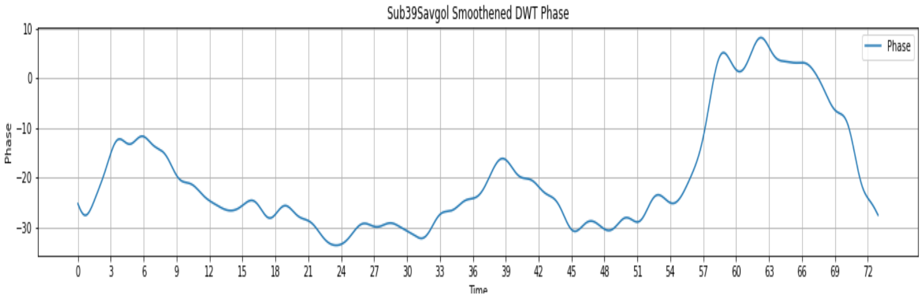

FIGURE 5.12: Stationary Data Subcarrier 40 Phase after denoising with DWT

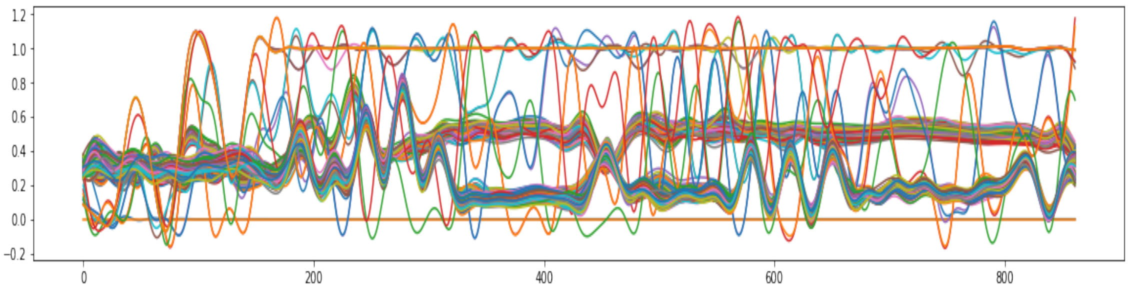

FIGURE 5.13: Stationary Data All subcarriers compressed Amplitude after denoising

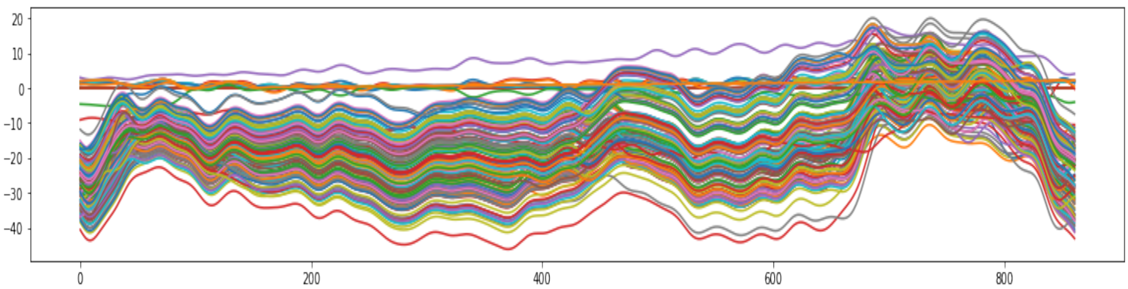

FIGURE 5.14: Stationary Data All subcarriers compressed Phase after denoising

5.3.2 Subject 1 Distraction Free and Watching Movie

We applied the same signal processing techniques to the data we collected initially. We present the results and plots below.

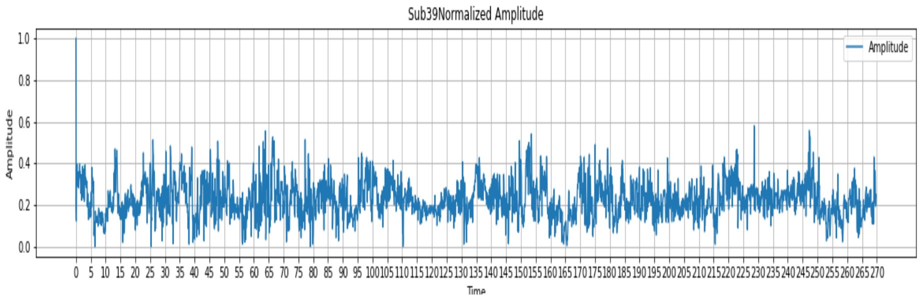

FIGURE 5.15: Subject1 Distraction Free Subcarrier 40 Amplitude after normalizing

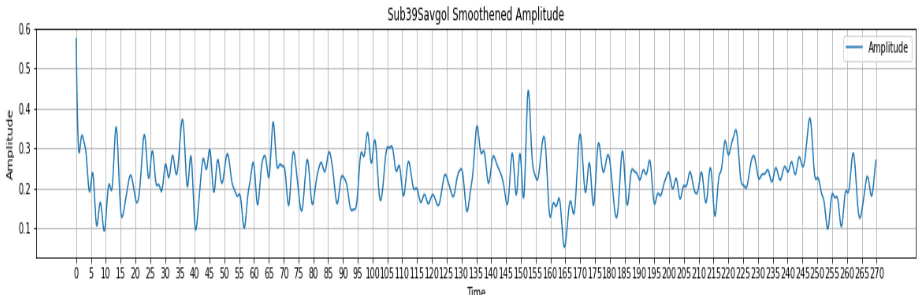

FIGURE 5.16: Subject1 Distraction Free Subcarrier 40 Amplitude after Savgol Filter

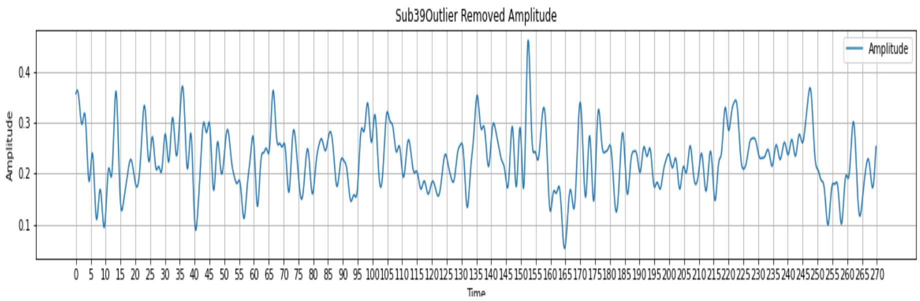

FIGURE 5.17: Subject1 Distraction Free Subcarrier 40 Amplitude after Outlier Removal

These results and the generated plots would help us investigate further and recognize and remove any linear or non-linear errors.

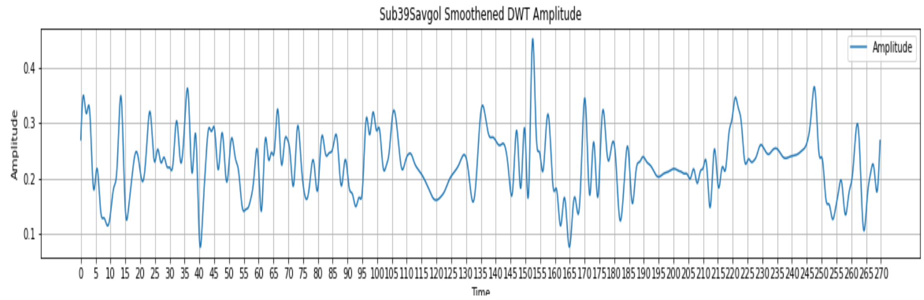

FIGURE 5.18: Subject1 Distraction Free Subcarrier 40 Amplitude after denoising with DWT

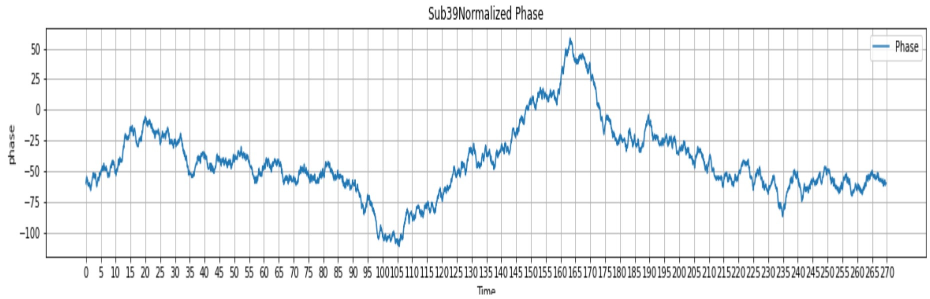

FIGURE 5.19: Subject1 Distraction Free Subcarrier 40 Phase after normalizing

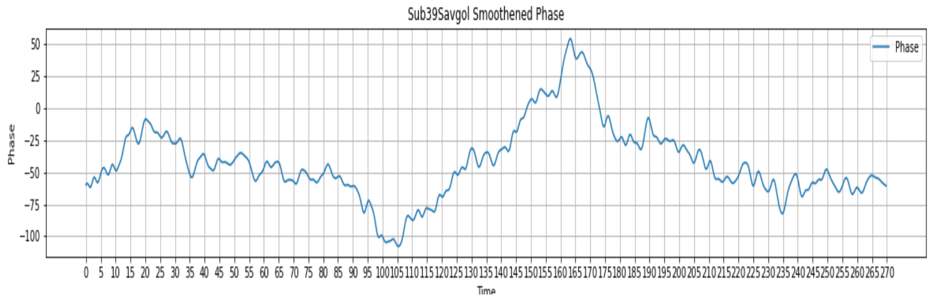

FIGURE 5.20: Subject1 Distraction Free Subcarrier 40 Phase after Savgol Filter

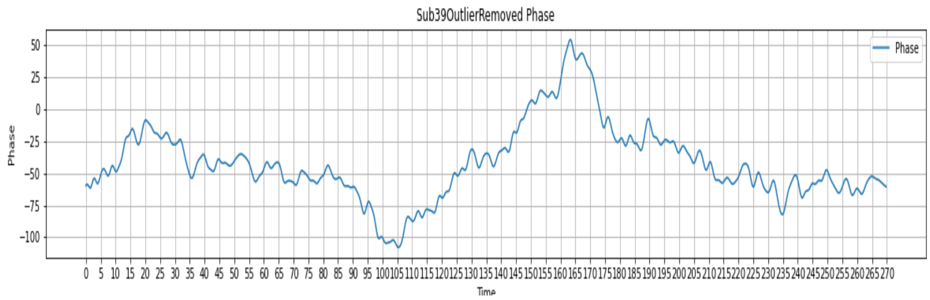

FIGURE 5.21: Subject1 Distraction Free Subcarrier 40 Phase after Outlier Removal

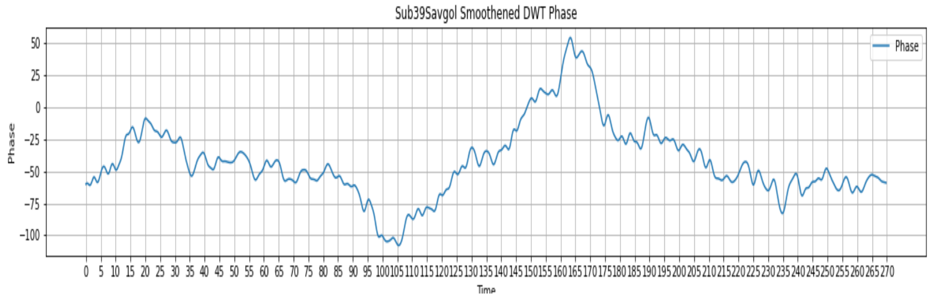

Figure 5.22: Subject1 Distraction Free Subcarrier 40 Phase after denoising with DWT

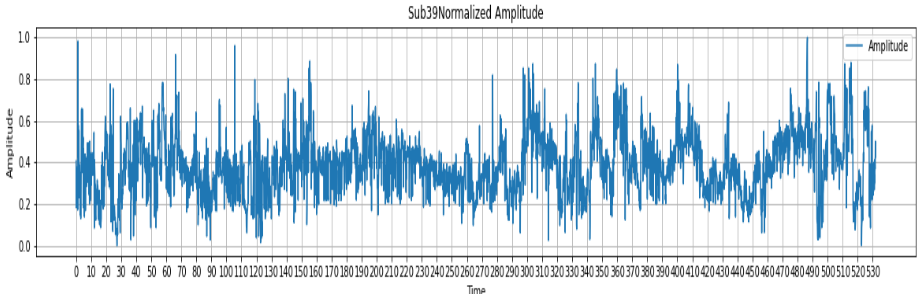

Figure 5.23: Subject1 Watching Movie Subcarrier 40 Amplitude after normalizing

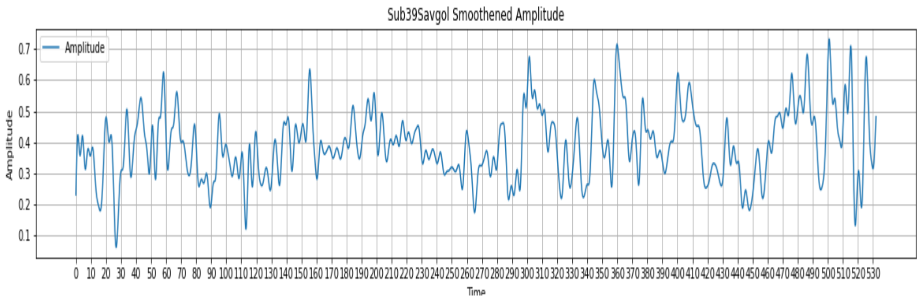

Figure 5.24: Subject1 Watching Movie Subcarrier 40 Amplitude after Savgol Filter

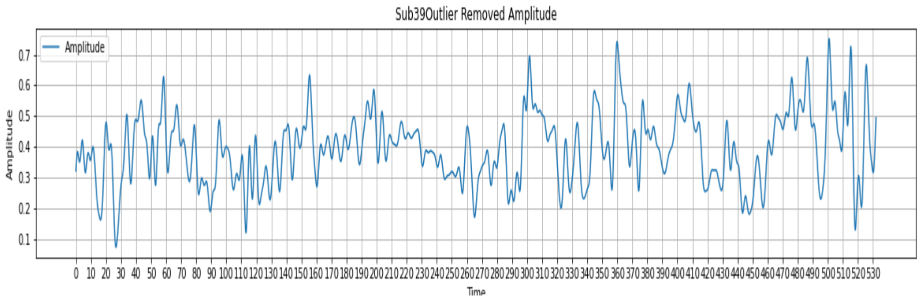

Figure 5.25: Subject1 Watching Movie Subcarrier 40 Amplitude after Outlier Removal

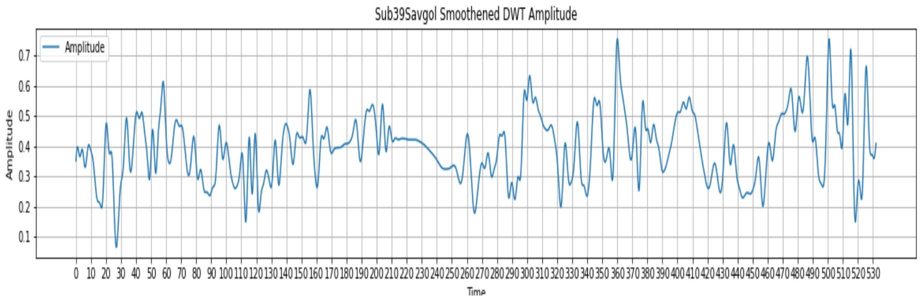

FIGURE 5.26: Subject1 Watching Movie Subcarrier 40 Amplitude after denoising with DWT

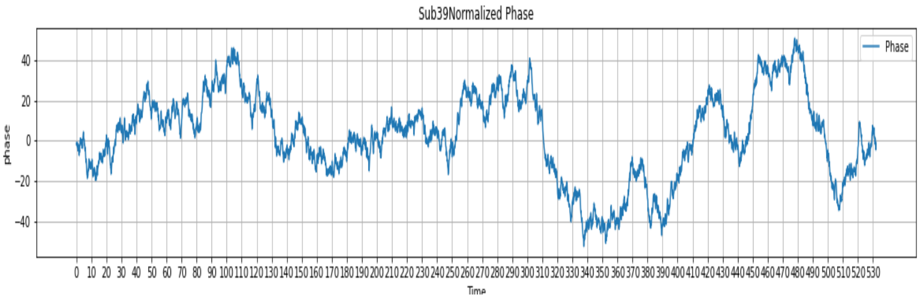

FIGURE 5.27: Subject1 Watching Movie Subcarrier 40 Phase after normalizing

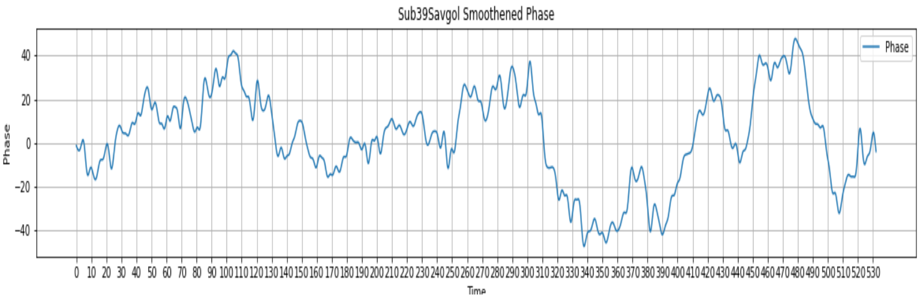

FIGURE 5.28: Subject1 Watching Movie Subcarrier 40 Phase after Savgol Filter

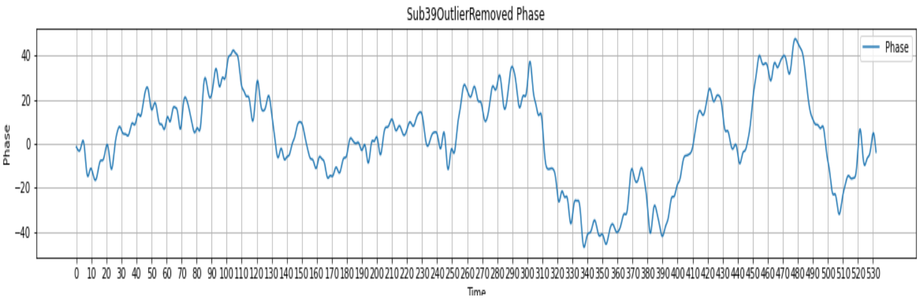

FIGURE 5.29: Subject1 Watching Movie Subcarrier 40 Phase after Outlier Removal

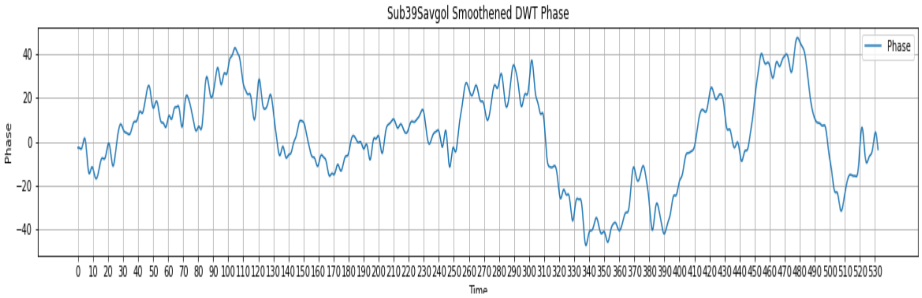

FIGURE 5.30: Subject1 Watching Movie Subcarrier 40 Phase after denoising with DWT

Chapter 6

Conclusion and Future Work

We tried to present or develop a framework that would help us estimate workout trends and warn users of downtrends. We try to do this with Channel State Information from devices we use daily. In this process, we realized that perceiving accurate information from CSI data is a challenge and that we need to employ extensive data processing to extract any efficacious artefacts. We found out that there can be error sources during the measurement of CSI data. Some of these errors like Carrier Frequency Offset, Sampling Frequency Offset, and Phase Ambiguity might hamper the accuracy of any study. Linear and non-linear errors in CSI phase values are challenging as well, and we need to take care of them. Future works can focus on comparing the data from each subcarrier and trying to correlate the phase response with any vital signs that our body displays while exercising.

Bibliography

[1] Espressif documentation channel state information. https://docs.espressif.com/projects/esp-idf/en/latest/esp32/api-guides/wifi.html#wi-fi-channel-state-information, 2016.

[2] Healthline. https://www.healthline.com/health/fitness-exercise/cardio-exercises-list, 2016.

[3] Heba Abdelnasser, Khaled Harras, and Moustafa Youssef. A ubiquitous wifi-based fine-grained gesture recognition system. *IEEE Transactions on Mobile Computing*, 18(11):2474–2487, 2019. doi: 10.1109/TMC.2018.2879075.

[4] Riccardo Crepaldi, Jeongkeun Lee, Raul Etkin, Sung Ju Lee, and Robin Kravets. Csi-sf: Estimating wireless channel state using csi sampling & fusion. In *2012 Proceedings IEEE INFOCOM, INFOCOM 2012*, Proceedings - IEEE INFOCOM, pages 154–162, June 2012. ISBN 9781467307758. doi: 10.1109/INFCOM.2012.6195523. IEEE Conference on Computer Communications, INFOCOM 2012 ; Conference date: 25-03-2012 Through 30-03-2012.

[5] Daniel Halperin, Wenjun Hu, Anmol Sheth, and David Wetherall. Tool release: Gathering 802.11n traces with channel state information. *ACM SIGCOMM CCR*, 41(1):53, Jan. 2011.

[6] Steven M Hernandez and Eyuphan Bulut. Lightweight and standalone IoT based WiFi sensing for active repositioning and mobility. In *21st International Symposium on "A World of Wireless, Mobile and Multimedia Networks" (WoWMoM) (WoWMoM 2020)*, Cork, Ireland, June 2020.

[7] Hao Kong, Li Lu, Jiadi Yu, Yingying Chen, Linghe Kong, and Minglu Li. Fingerpass: Finger gesture-based continuous user authentication for smart

homes using commodity wifi. In *Proceedings of the Twentieth ACM International Symposium on Mobile Ad Hoc Networking and Computing*, Mobihoc '19, page 201–210, New York, NY, USA, 2019. Association for Computing Machinery. ISBN 9781450367646. doi: 10.1145/3323679.3326518. URL https://doi.org/10.1145/3323679.3326518.

[8] Hoonyong Lee, Changbum R. Ahn, Nakjung Choi, Toseung Kim, and Hyunsoo Lee. The effects of housing environments on the performance of activity-recognition systems using wi-fi channel state information: An exploratory study. *Sensors*, 19(5), 2019. ISSN 1424-8220. doi: 10.3390/s19050983. URL https://www.mdpi.com/1424-8220/19/5/983.

[9] Yongsen Ma, Gang Zhou, and Shuangquan Wang. Wifi sensing with channel state information: A survey. *ACM Comput. Surv.*, 52(3), jun 2019. ISSN 0360-0300. doi: 10.1145/3310194. URL https://doi.org/10.1145/3310194.

[10] Hannaneh Barahouei Pasandi and Tamer Nadeem. Latte: Online mu-mimo grouping for video streaming over commodity wifi. In *Proceedings of the 19th Annual International Conference on Mobile Systems, Applications, and Services*, MobiSys '21, page 491–492, New York, NY, USA, 2021. Association for Computing Machinery. ISBN 9781450384438. doi: 10.1145/3458864.3466913. URL https://doi.org/10.1145/3458864.3466913.

[11] Harsh Pritam. Link to onedrive. https://iitkgpacin-my.sharepoint.com/:f:/g/personal/harshpritam_iitkgp_ac_in/Er5G--W730VCjPn779_lrr0BsYSrj8V0q-N6Xnn5Zqei9A?e=3kkbdW, 2022.

[12] Meera Radhakrishnan, Archan Misra, and Rajesh K. Balan. W8-scope: Fine-grained, practical monitoring of weight stack-based exercises. *Pervasive and Mobile Computing*, 75:101418, 2021. ISSN 1574-1192. doi: https://doi.org/10.1016/j.pmcj.2021.101418. URL https://www.sciencedirect.com/science/article/pii/S1574119221000699.

[13] Xuyu Wang, Chao Yang, and Shiwen Mao. On csi-based vital sign monitoring using commodity wifi. *ACM Trans. Comput. Healthcare*, 1(3), may 2020. ISSN 2691-1957. doi: 10.1145/3377165. URL https://doi.org/10.1145/3377165.

[14] Jieming Yang, Yanming Liu, Zhiying Liu, Yun Wu, Tianyang Li, and Yuehua Yang. A framework for human activity recognition based on wifi csi signal

enhancement. *International Journal of Antennas and Propagation*, 2021:1–18, 02 2021. doi: 10.1155/2021/6654752.

[15] Yanqing Zhang, Jiankang Zhang, Yongkai Huo, Chao Xu, Mohammed El-Hajjar, and Lajos Hanzo. Scalable panoramic wireless video streaming relying on optimal-rate fec-coded adaptive qam. *IEEE Transactions on Vehicular Technology*, 69(10):11206–11219, 2020. doi: 10.1109/TVT.2020.3008384.