UNIVERSITY OF TWENTE.

Faculty of Electrical Engineering, Mathematics & Computer Science

Unobtrusive sensing using Wi-Fi signals

Prachi Bagave

M.Sc. Embedded Systems Thesis
August 2018

Supervisors:
Prof. Dr. Ir. Paul Havinga
Dr. Ir. D.V. Le Viet Duc

Pervasive Systems Group
Faculty of Electrical Engineering,
Mathematics and Computer Science
University of Twente
P.O. Box 217
7500 AE Enschede
The Netherlands

Acknowledgement

This thesis is a part of 'Create Health' project at the Pervasive Systems research group, University of Twente. I started working on it from January 2018. It serves to be an initial step for using WiFi as a means of unobtrusive sensing within this project. We headed with a rather challenging approach and also aimed at making a workable demonstration at the same time. This shaped the thesis in a little different way than expected. But overall it turned out to be an interesting and lively experience for me. For that, I would like to thank everyone who contributed in making my journey successful.

Firstly, I would like to convey my deepest gratitude to Prof. Dr. Paul Havinga, my supervisor who gave me an opportunity to work under this project. He always motivated me to tackle the research questions in a progressive way. This helped me understand the system and plan my work in a systematic manner.

I would also like to express my sincere thanks to my daily supervisor Dr. Ir. Viet Duc. His enthusiasm, advices and technical support encouraged me to take up the challenges sportingly and opened new ways of solving the problem.

As a part of the work I also performed experiments at the anechoic chamber of RF Lab, Integrated Circuit Design (ICD) group, University of Twente. I would like to thank Ing. Henk De Vries for giving me an opportunity to use the chamber and other equipments. Experiments in the anechoic chamber have been an added bonus to the work.

I would also like to extend my thanks to all the members of Pervasive System who made a comforting and friendly work environment. I enjoyed working with the group, small coffee breaks and the little chit chats over work.

Finally, I would like to acknowledge with gratitude, the love and support of my friends and family. It kept me going through all the odds and helped finish this work in time.

Abstract

Detecting human activities has been an actively growing research area since a few decades. It opens a wide area of applications in health care, robotics, human-media interaction, surveillance and sports. People have started accepting these technologies, either as logging their step counts or even monitoring their baby's sleep cycle. The drawback of such devices is that each device with a different purpose comes with a new hardware and thus indulges additive costs. This project proposes to use WiFi for a device-free low-cost activity recognition system as it is easily available in offices and homes now a days. It is also ubiquitous in nature as it collects information from the environment while providing Internet. The underlying idea behind this approach is to acquire and model the changes in the multi-path WiFi radio waves due to human motion. The existing systems are based on a few basic activities like sitting, standing, running or walking for which machine learning models are trained and used for classification. This project attempts to find a more generic approach for activity recognition. Each activity is considered as a sequence of discrete static postures over time. For example walking, jogging and running are combination of same postures at different pace. The project mainly focuses on reliability of a particular application so that it could be used in real time. It is observed that static postures have limited features and are more dependent on the environmental factors and system fluctuations than dynamic activities hence less reliable.

Summary

Tasks like surveillance, tracking patient behavior or monitoring one's activities for health-care need human involvement. With the help of Human Activity Recognition (HAR) it is now possible to automate such tasks. Many devices are getting emerged, either with the help of wearable sensor devices or collecting information from the environment also called as device free activity recognition. Examples of wearable devices are smart watches and smart bands whereas examples of device free activity recognition are predicting criminal or dangerous activities during surveillance at public places and automatic appliance control in smart homes. Device free activity recognition is advantageous in the sense that the user does not have to face discomfort by wearing devices on the body and the system is more ubiquitous in nature. On the other hand it is challenging as it is collecting the information from the environment and thus more susceptible to noise.

In this project we introduce an activity recognition system which uses WiFi radio signals for detecting the activities. This is a low cost unobtrusive device free activity recognition system. Since WiFi is easily available in the offices and homes these days, such a system could be built without including much cost. The underlying phenomenon behind this system is to model the changes in the multi-path WiFi radio waves caused due to human motion. Existing work shows that it is possible to model activity recognition system for day to day activities like sitting, standing, running and walking. Classifying such activities are possible since they differ in speeds and duration of the activity. This project proposes a generalized approach which could include a variety of activities. Each activity is considered as a sequential combination of static postures. Thus we aim at having static posture recognition for this project. The challenges for such a system is that the system is to be built on static instant values as there are no features which vary over time. Thus there are limitations over feature selection.

In this project we use IEEE 802.11n as the Wifi protocol. This protocol uses 2.4 or 5 GHz frequency band with a bandwidth of 20 or 40 MHz. Within this bandwidth it has multiple channels with narrow-band sub-carriers which carry the data for wireless communication. For IEEE 802.11n Orthogonal Frequency Division Multiplexed (OFDM) is used as the multiplexing technique which provides digital multi-carrier propagation with closely spaced carriers. In a usual room, the sub-carriers undergo multi-path effect due to reflection, absorption or diffraction along the surfaces of walls and furnitures. This might cause constructive or destructive interference at the receiver end. Usually, disturbances in WiFi are measured by Received Signal Strength Indicator (RSSI) value which is nothing but the strength of the received signal compared to the transmitted signal. This could also be viewed as the sum of strengths of all the sub-carriers. When a person moves, multi-paths change, and RSSI values seem to be fluctuating and may not give enough information for activity recognition. Recently, Channel State Information (CSI) is being used for activity recognition. CSI is strength of the individual sub-carriers. Thus it is more informative than the RSSI and has a potential to be used for detailed activity recognition.

Before performing the experiments it is important to understand the behavior of the data being used. Thus the first step in this project assignment is to get acquainted with the CSI data and understand its dependencies on various environmental factors in an experimental setup. For that we set up a simple WiFi system consisting of a transmitter and a receiver in a usual office room. Then the CSI packets parameters relevant to this project are studied. Particularly the time stamp of each packet, packet delivery and CSI data are studied. The CSI value is profiled for long term and short term time duration. For short term, CSI is observed to be affected by Automatic Gain Control (AGC) and for long term it is suspected to be affected by some uncontrollable environmental factors.

For activity recognition, this project focuses on single person activities and first handles simple activity recognition then moves to difficult ones. Both dynamic and static activity detection are performed so that it is possible to compare them on the basis of feature extraction, classification accuracies and stability of the system. Initially a system similar to intrusion detection is performed which detects whether a person is moving or not. Then we switch to another dynamic activity recognition which is to detect shapes made by finger tips in the air. This includes simple shapes like straight lines, diagonals and circles. Then we move to static posture recognition which includes 5 exercise postures with different hand and leg positions. It is observed that dynamic activities could be classified on the basis of their time varying features like shapes, peaks or variance. But the static postures have limited features based on their instantaneous values. Static postures are also dependent on other environmental conditions and fluctuations of the WiFi System.

Contents

List of acronyms

CSI	Channel State Information
RSSI	Received Signal Strength Indicator
TOF	Time of Flight
DTW	Dynamic Time Warping
DWT	Discrete Wavelet Transform
CWT	Continuous Wavelet Transform
OFDM	Orthogonal Frequency Division Multiplexed
MIT	Massachusetts Institute of Technology
FMCW	Frequency Modulated Career Wave
PSK	Phase Shift Keying
ASK	Amplitude Shift Keying
CCK	Complementary Code Keying
SVR	Short-term Averaged Variance Ratio
LVR	Long-term Averaged Variance Ratio
CFR	Channel Frequency Response
PCA	Principle Component Analysis
HMM	Hidden Markov Model
LSTM	Long Short Term Memory
MIMO	Multiple Input Multiple Output
NIC	Network Interface Card

AGC Automatic Gain Control

MAC Media Access Control

AP Access Point

HT High Throughput

HAR Human Activity Recognition

Chapter 1

Introduction

During past few decades, the growing lifestyle deceases have been a concerning issue and measures are been taken against it [1]. People are getting aware and monitoring their activities and diet to keep their health on track. This is also inspiring a number of researches to be carried out for automatic human motion detection. Motion detection could either be used merely to detect the movement of people stuck in debris in case of earthquakes or it may be activity recognition to monitor ones health conditions. Some of the common devices used for activity recognition these days are the smart bands [2] to track number of steps taken by individuals, kinect [3] used in xbox-one gaming console, and automatic control of lights in smart homes. These devices are already in the market and researchers are consistently working to bring out more such applications with better solutions. In 2013, researchers from Massachusetts Institute of Technology (MIT) introduced RF-capture [4] which could detect the human figure through the wall using RF signals. In the same year, Wisee [5] was also in the BBC news as they could detect and recognize gestures using Wi-Fi signals. Since Wi-Fi is available commonly in houses and offices now-a-days, we can build a low cost activity recognition system. Wi-Fi signals can also pass through the wall, making it possible to have through the wall detections. One could question if this might violate privacy issues, which is why it becomes important to understand the extent to which activity recognition is possible using such a system.

1.1 Motivation

Existing techniques for activity detection use wearable devices [6], camera based system [3] or radio signals based systems [7], [8]. Among these, device-free motion detection systems are more convenient to use since they are ubiquitous in nature and people do not have to face any inconvenience by wearing devices. Also, within the device free systems, radio systems have an advantage over camera based systems as they do not have to depend on light conditions and are not affected by physical obstacles. Systems based on cameras may also cause privacy issues and hence are not suitable in a lot of scenarios.

In this paper we focus only on the radio based systems, especially the WiFi. A variety of applications based on WiFi may be classified on the basis of the granularity of information being processed. Some application areas use coarse grain information where it just detects if the human is moving or not. For example intrusion detection [9] which detects presence of an intruder when you are not home or counting human flow [10] used to control human traffic. Other applications use fine grained information to detect different activities. For example fall detection at elder care homes [11] and human identification using individual's gait features [12]. Applications like keystroke detection [13] or heart-rate detection [14] focus on even finer granularity by focusing only on the movement of particular body parts like fingers or breathing movements.

In this project we focus on day to day activities. An activity is considered to be a sequence of continuous static postures. Similar to the analogy of a video, composed of image frames taken at discrete time instances, an activity could be viewed as a composition of static postures over time. Thus we primarily aim at detecting static postures of people. The idea is to continuously detect static postures in order to infer the total activity performed by a person. It is also important to analyse whether such a system is suitable over a dynamic activity recognition system. Thus we first build some simple dynamic activity recognition systems and then compare it with the static one.

1.2 Framework

In order to build the activity recognition system we set up a Wi-Fi system consisting of an Access Point (AP) and a receiver in the meeting room of our work area. A few pre-decided activities were used in the experiments. Each experiment consisted of a particular activity being performed in between the transmitter(AP) and the receiver for a few seconds. During this time, the CSI of the Wi-Fi signal was traced and saved in the database. Multiple trials of such experiments were carried out at different times and days. Later machine learning algorithms were used to classify between the activities.

1.3 Research questions

The research questions for this study may be framed as follows:

1. Is it possible to recognize static postures using CSI of Wi-Fi signals?
   (a) If yes, how well could it be recognized?
   (b) What could be the distinct features for static postures?
2. Can we find a structure for the unstructured Wi-Fi data?
3. How well is the whole idea of recognizing the activities as a sequence of static postures?
   (a) Is it implementable in real time?
   (b) Is it more feasible to have activity recognition as sequence of static postures than dynamic activity recognition?

1.4 Report organization

The remainder of this report is organized as follows. Chapter 2 describes the different attributes of WiFi like RSSI, CSI and TOF and reasons how CSI is more informative than the other two attributes for activity recognition. It also explains in detail state of the art systems on the basis of their granularity. Chapter 3 summarizes the behavior of the CSI data and studies the reliability of the information provided by the CSI packets. Chapter 4 describes the experiments, methodologies and results for different dynamic and static activity recognition systems. Finally, Chapter 5 concludes the project and provides some points for future work.

Chapter 2

Literature Survey

A simple WiFi system could be considered of a transmitter-receiver pair where WiFi radio waves travel from the transmitter to the receiver. The propagation of the signals could be thought similar to ripples created on a water surface, but in 3 dimensions. Thus, WiFi radio waves in a usual office room get reflected, absorbed and diffracted from the walls, furniture and people present in the room which causes multi-path effect. as a result the amplitude, phase and path length of the signals also change. Using these properties, it is possible to detect the effect of human activities on the signals. In this chapter we study the attributes of Wi-Fi signals which may be used for activity recognition in Section 2.1 and then study the existing work under Section 2.2.

2.1 Wi-Fi properties

This section describes the attributes of WiFi signal which could be used to extract information about human motion. There are three attributes which are explained below as RSSI, CSI and TOF [15].

2.1.1 RSSI

RSSI is the MAC layer information of Wi-Fi representing the strength of the received signal compared to the transmitted signal. In a typical room with furnitures, when a signal gets transmitted, it gets reflected by different surfaces and reaches the receiver. RSSI is given as the superposition of all these multi-path signals received. Due to differences in the followed path, multi-path components have different delay, attenuation and phase shift [15]. The figure 2.1 shows an example of the multi-paths and resulted signal received at the receiver.

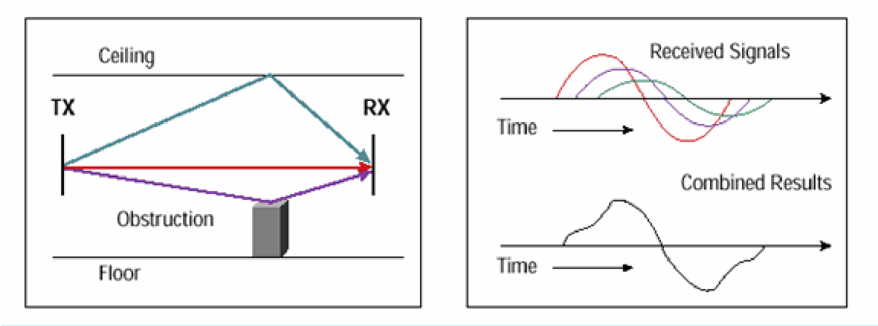


Figure 2.1: Multi-paths in Wi-Fi signals [16]

The complex baseband voltage at the receiver end may be given as [15]:

$$V = \sum_{i=1}^{N} ||V_i||\, e^{-j\theta_i} \tag{2.1}$$

where V_i and θ_i are amplitude and phase of the i^{th} multi-path component and N is the total number of components. The $RSSI$ could be given as the power of the received signal as:

$$V = 10\, log_2||V||^2 \tag{2.2}$$

It could be seen from equation 2.1 that each multi-path component contributes to the RSSI value. A slight change in environmental conditions may cause multi-path components to add up in constructive or destructive manner. Hence there are fluctuations cased by moving bodies and changes in the RSSI values cannot be modeled w.r.t. the moving bodies [17].

Mohamed Hadi Habaebi et all [18] provide an intrusion detection system based on RSSI of the Wi-Fi signals. Later, they also use this information to turn On/Off the household devices. The system depends on the distance between the transmitter and receiver and a high false alarm rate was detected with increasing distance. The system used Wi-Fi NIC card along with Arduino Uno micro-controller and two relays to control the lights and Air-conditioner of one of the Offices. It also used Zig-bee motes to characterize the signal behavior. It uses variance of RSSI of an empty room to compare with the variance of RSSI under testing conditions. If the variance is detected to be higher than the calibrated empty room variance, it detects a presence of a person.

RASID [19] is also a motion detection system based on RSSI value. Similar to intrusion detection system in [18], RASID also generates normal profile of the system when the room is empty and compares it with the profiles in presence of intruder. To make the system robust, it also updates the normal profile whenever the empty room is slightly changed. Both the applications merely detect the presence of a person in a room and work on variance of the RSSI values.

2.1.2 CSI

Channel state information is the physical layer information of the Wi-Fi signal. For OFDM Wi-Fi signals, CSI gives the channel response of the system. In contrast with the RSSI information, CSI gives the information of different channels instead of a cumulative signal strength indication. Hence frequency selective fading could be observed as loss of information from particular channels and so CSI is more informative than RSSI. The Figure 2.2 shows the analogy between the RSSI and CSI for better understanding.

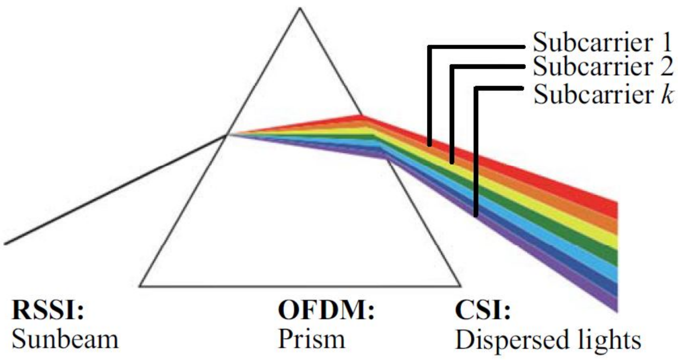


Figure 2.2: An analogous representation of CSI and RSSI [15]

Wireless communication systems undergo attenuation, delays and phase shifts. In order to maintain the rate adaptations and transmit power, wi-fi devices have to continuously monitor the channel state for each MIMO channel [20]. The narrow-band flat fading channel model of MIMO system is given by [20]:

$$Y = H \times X + N \tag{2.3}$$

where Y represents the received signal vector, X represents the transmitted signal vector, N represents the noise signal vector and H represents the channel state matrix. CSI is nothing but the H matrix which represents the channel frequency response the system for each sub-carrier. In an MIMO system with N_T number of transmit antennas, N_R number of receive antennas and N_C number of channel sub-carriers, CSI is a 3-dimensional matrix with a size of $N_T \times N_R \times N_C$. Each element in the matrix is a complex number with the amplitude and phase information of corresponding receiver-transmitter pair of antennas for particular OFDM sub-carrier. The

H matrix could be mathematically represented as

$$H = \begin{bmatrix} H_{11} & H_{12} & H_{13} & \dots & H_{1N_R} \\ H_{21} & H_{22} & H_{23} & \dots & H_{2N_R} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ H_{N_T1} & H_{N_T2} & H_{N_T3} & \dots & H_{N_TN_R} \end{bmatrix} \tag{2.4}$$

where $H_{ij} = h_1, h_2, h_3 \cdots h_{N_C}$ is the CSI value for transmitting antenna i and receiving antenna j; and h_k denotes channel sate for k^th sub-carrier [20]. Each complex h_k could also be represented by

$$h_k = |h_k|\, e^{j \sin\theta} \tag{2.5}$$

where $|h_k|$ represents the amplitude and θ represents the phase. Applications for CSI are discussed in detail in Section 2.2.

2.1.3 TOF

Time of flight is the time attribute of radio signal which provides the measurement of time taken by the signal to travel to an obstacle, reflect and come back. The distance of the obstacle can then be simply found out by multiplying TOF with the speed of light. The speed of human movement can then be achieved by measuring the variations in distance of the object over time.

Frequency Modulated Career Wave (FMCW) signals can produce narrow band signals with a few kilo Hertz of bandwidth, keeping the frequency sweep linear to the time [20]. The Figure 2.3 shows the frequency-time relation of FMCW:

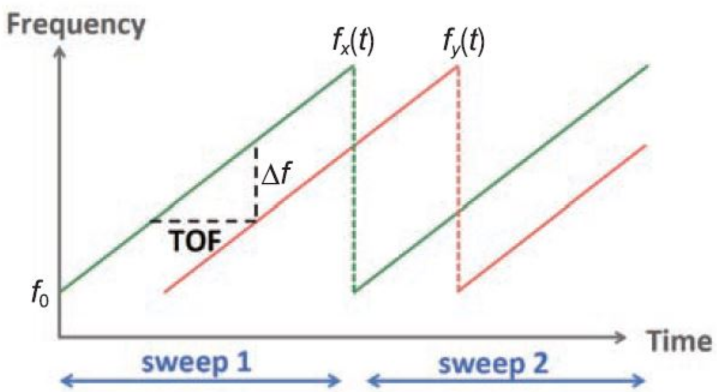


Figure 2.3: FMCW signal: FMCW signal after reflection produces a time delayed signal. Linear sweep in frequency helps in finding the tie delay. [20]

Due to the linear nature, the round trip distance to the obstacle can be measured as 2.6:

$$D_{round\,trip} = c \times TOF = c \times \frac{\Delta f}{slope} \tag{2.6}$$

WiTrack [7] and WiTrack2.0 [8] designed by MIT can localize people using FMCW technology through the walls. WiTrack had a limitation that it could only track 1 person at a time which was later overcome by WiTrack2.0 developed for tracking multiple people. WiTrack2.0 could detect 4 moving persons or 5 static persons within an area of 10 meter square from the system. The system uses FMCW technique which sweeps frequencies between 5.46GHz and 7.24GHz. The system uses time of flight, phase of RF signal and spatial direction for calculating distance and direction of the human movement.

Later with RF-Capture [4], also by MIT they came up with system to capture a coarse skeleton of human body. It captures body parts as head, body trunk and the limbs and stitches these parts to form the whole skeleton. It can also identify 15 different people with an accuracy of 88%. It can also detect English alphabets drawn in air using hand with maximum error of around 5cm. The drawback of this system is that is expects the subject to walk towards the RF capture system.

To measure TOF in Wi-Fi systems signals need to be modulated using FMCW technique. But current off the shelf Wi-Fi systems like 802.11 b/ac/n work on Phase Shift Keying (PSK), Amplitude Shift Keying (ASK) or Complementary Code Keying (CCK) technique [21]. Hence using TOF with Wi-Fi systems is not a convenient approach.

2.2 Related Work

The state of the art approaches using wi-fi to detect human activities could be classified as coarse-grain, fine-grain or super fine grain activity detection. Applications using coarse grain detection detect only the presence of human movement. For example in intrusion detection, the application has to detect presence of a moving person. Fine grain applications focus on detecting the type of movements. Example of a fine grain application could be detecting human activities such as running, walking or falling down. If the application focuses on movement of a particular body part such as detecting movement of chest while breathing to monitoring heart-beat rate, is classified as super-fine grain activity detection. In this section, we would go through different state of the art approaches to achieve activity detection at these three granularity levels.

2.2.1 Coarse-Grain Activity Detection

RASID [19] and intrusion detection system by Mohamed Hadi Habaebi et all [18] are the examples of applications which detect the presence of a person with the help of RSSI. These systems are already discussed in Section 2.1.1.

Intrusion detection by Gong, L. et all [22] proposes a CSI based real-time calibration-free device-free passive human motion detection. The system is independent of indoor scenarios and needs no prior-calibration and normal profile. It extract ratio of Channel Frequency Response (CFR) phases between adjacent packets as basic feature. To detect real time human motion, it uses two types of coefficient of variance of phases: Short-term Averaged Variance Ratio (SVR) and Long-term Averaged Variance Ratio (LVR). It demonstrates how phase of CFR is more sensitive to human movement than its amplitude. It later compares the results with RSSI based approach and amplitude of CSI based approach.

Another paper by Kun Qian et all [23] which also proposes a method to detect human motion using CSI value from the wi-fi signal. They explore more on the space diversity offered by multi-antenna systems now-a-days in MIMO systems. They use amplitude, phase and space diversity of the wi-fi signal to detect moving people irrespective of their walking speeds. The phase differences across different antennas are used as phase information. This method of data extraction is experimentally proved to reduce the noise disturbances on phase. An outliers method is used to reduce the effect of noise on amplitude information. And the first two significant Eigen values of correlation matrix of CSI are used for feature extraction. This method achieves almost 99% true detection with no false detection.

Identification of person using coarse-grain information

On the contrary to intrusion detection, Avinash Kalyanaraman et all [24] proposes a system to track people based on body shapes. This is a radar based system which used pulsed radar system to detect the energy of a signal reflected from moving human body. The paper claims that body shape is a stronger biometric than height, weight and width of a person. The radio system used has a range of about 1 meter and is used to detect people passing by a door having a radio transmitter just above the door frame. To detect the moving person it uses Doppler shift and head distance from the radar system. And to get the body shape it uses radar frame power as a function of distance from the radar system. Although the system does not get create a full shape of the body because of the short range of the radar and the positioning of the system right above the door frame, it uses the radar frame energy as a direct correspondence with the body shape. In a house of 4 people this system has an accuracy of around 78%.

2.2.2 Fine-Grain Activity Detection

Fine grain activities could be further classified on the basis of their functionality as activity recognition and identification of a person.

Activity recognition

Yi Wang et all [25] suggest a system to detect human activities using the properties of CSI of wi-fi Multiple Input Multiple Output (MIMO) radios. It can detect movements insensitive to location, orientation and speed using a pair of wi-fi transmission points and access points. For evaluation, it uses 24 dimensional features and selects the strongest 14 features by feature selection. Linear Discriminant Analysis (LDA) and support vector machines (SVM) are compared for classification algorithms. The best results for action detection are found to be using feature selection and multi-class SVM. This system is capable of detecting actions like squatting, sitting, standing up and falling down and is unable to detect small motion actions like cooking, eating, watching TV and so on.

Wei Wang et al [26] propose an activity recognition system by modeling the correlation of CSI dynamics with human activities. It introduces CSI speed model which quantifies the relation between human speed of movement and CFR power of all the channels and CSI activity model which relates speed of movement and type of action. The principle behind the CSI speed model is that when the lengths of multi path change due to human motion, CFR power changes according to the change of path length. It is observed that the higher speed movements have a greater affect on the higher frequency channel and low speed movement have effect on the lower frequency. An example of this can be observed in the Figure 2.4 where walking has continuous high frequency components than sitting or falling and falling has a high frequency component for very small duration. The transition from lower speed of movement to higher or vice versa is modeled by Hidden Markov Model (HMM). HMMs are trained by de-noised CSI signals from a number of activities. The paper proposes Principle Component Analysis (PCA) to reduce the dimensionality and remove the noisy components. The proposed system achieves a cross validation accuracy of 96.5% for 7 different activities namely, running, walking, sitting down, opening refrigerator, falling, boxing, pushing one hand, brushing teeth and no activity. The drawback of the system is that it has been validated for single person scenario.

On the similar lines as CARM [26], Siamak Yousefi et all [27] explores deep learning methods instead of machine learning techniques used in CARM. It uses Long Short Term Memory (LSTM) for training and classification of the activities and compares it with HMM and Random Forest method. The experimental results show

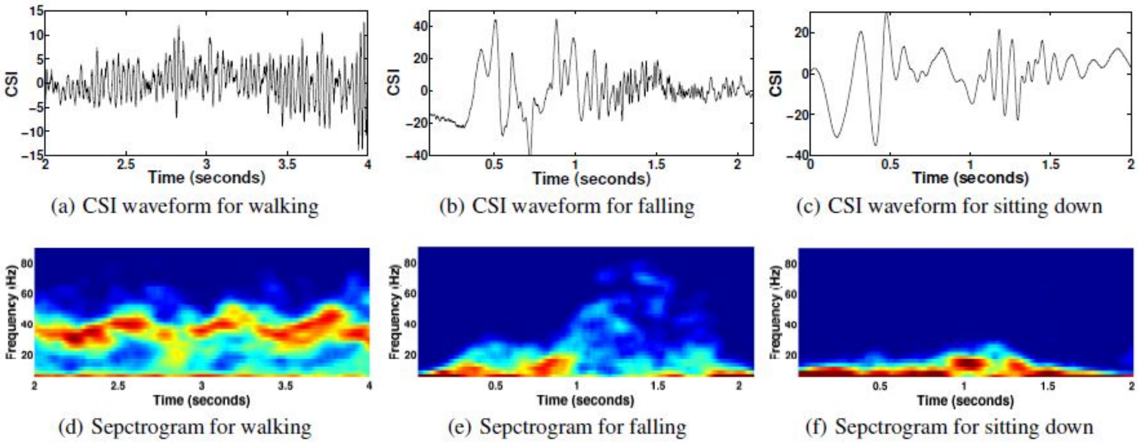


Figure 2.4: Activity-speed model in CARM [26]

that the accuracy of LSTM is higher than the other two and could even distinguish well between similar activities like sitting, standing and lying down. Since the data is not pre-processed it takes high training time compared to HMM.

Identification of person using fine-grain information

Wi-Fi-ID [28] gives an another example of human identification with the use of CSI signals. It proposes that unique gaits of a person may be detected from the energy distribution in the frequency band 20-80 Hz compared to other frequencies. It uses Continuous Wavelet Transform (CWT) to get signals in the different frequency bands with respect to time and uses ReliefF as feature extraction method. The experiment is done on 20 subjects in a corridor with one person walking at a time. It uses sparse approximation based classification (SAC) as the classification algorithm and used 10 fold cross validation to evaluate the accuracy. The system has an accuracy of 93% to 77% when the group size goes from 2 to 6 people.

FreeSense [29] is another system which identifies different people in a house using the CSI information. Similar to [28], it also uses the variations in CSI caused due to walking patterns of different people. But it claims to achieve much higher accuracies than Wi-fi-ID [28] of around 88.9% and 94.5% for a group of 6 and 2 persons respectively. It uses the CSI deformations when the people walk in the line of sight. It uses shapes of the extracted line-of-sight waveform as features and uses PCA to reduce the data dimensionality. It uses dynamic time warping to compare signals with different time features(length and variation over time).

Compared to free-Sense [29] and Wi-Fi-ID [28], Wei Wang et all [12] give a more general approach to distinguish between people based on their gaits using the CSI information. Using the CSI spectrogram, torso movement contour can be estimated by tracking the frequency with highest energy. The autocorrelation of such contours gives speed and cycle time of torso movement as important gait features. Author also uses footstep length and gait cycle time as important gait features. Figure 2.5 explains how people could be distinguished on the basis of torso speeds and step cycles per second. On similar lines, different spectrogram signatures may also be used as gait features. Energy distribution and its movement can serve as signature for human gait pattern. This paper also uses PCA to reduce the dimensionality and refine the noisy CSI signal. With 50 participants, the system has 8.05% false acceptance rate and 9.54% false rejection rate when using probability threshold for identification as 0.5.

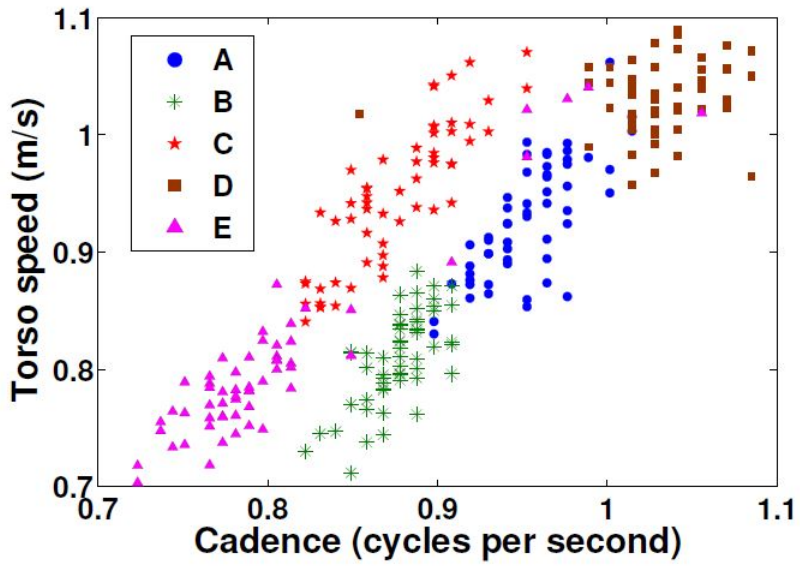


Figure 2.5: Distribution of Cadence and Torso speed [12]

2.2.3 Super-Fine-Grain Activity Detection

Kamran Ali et all [13] proposes a method to detect keystrokes using CSI of wi-fi signals. It observes that while typing the keystrokes are pressed in a specific periodic manner. It also observes that the signal deviations of different antenna pairs are closely related for a given keystroke. The system is built in a robust way using this information. It uses PCA to get principle components of the information about the changes in CSI caused due to keystrokes. Similar to [26] is avoids the 1st PCA component to avoid noisy components. It uses Discrete Wavelet Transform (DWT) to extract frequency vs time information and Dynamic time warping for classification. Dynamic Time Warping (DTW) used K-NN classifiers which works on finding smallest Euclidean distance between the time shifted waveforms for classification. The drawback of this system was that the shapes and amplitudes of signals change with change in distance, orientation of AP and receivers.

Other examples of super-fine-grained activity recognition are heart rate and breathing pattern monitors. TinySense [30] and Sangyoun Lee et all [14] provide examples of such applications which require very minute sensing of wi-fi CSI signals. According to TinySense, when people respire in Fresnel-zone there are periodic ups and downs in the CSI signal of wi-fi. Fresnel-Zones are concentric elliptic zones in a given pair of transmitter and receiver. The phase changes caused in the CSI is used as a measure of breathing pattern of a person. To deal with multi-person scenario, it uses a threshold for time of arrival of received signals by Multiple Input Multiple Output (MIMO) systems. In addition to the methods used by TinySense, Sangyoun Lee et all [14] use butterworth filter with a pass-band in the range of breathing frequencies(0.2-0.33 Hz) and heart rate frequencies(1-1.33 Hz) to detect them respectively. It also uses a reference breathing and heart rates (normal rate) of the person to compare it with various breathing and heart rates at different times. DTW is used to compare the signals. On the basis of heart rate of a person, it also detects various activities like running, walking, sleeping and resting with an accuracy of 95%.

2.3 Summary

Activity recognition using WiFi is getting matured by the emergence of finer activity recognition systems starting from intrusion detection to heart rate detection. Projects like [26] and [27] make it possible to model the effects of human motion on radio signals by defining the relation of speed with frequency. Out of the three main attributes of WiFi, CSI is more informative. The multi-dimensional CSI information makes it possible to detect very fine activities by proper filtering and signal processing methods.

Chapter 3

Profiling CSI data

WiFi data at 2.4GHz with a wavelength of 12.5cm gets reflected, absorbed and passes through different objects in a usual room with furnitures and concrete walls. This means that there are a lot of factors affecting the signals which make them unstructured. Thus, in this chapter we concentrate on the behavior of the signals.

From Chapter 2, it could be inferred that CSI has a potential to be used for activity recognition since it reflects change in values even for very fine activities. Thus this project also uses CSI for its experiments. For doing so, a simple WiFi system is set up, with a transmitter and a receiver. AP with two antennas is used as the transmitter and a Linux based system with a three antenna receiver. Off the shelf Intel 5300 Network Interface Card (NIC) along with 3rd party drivers [31] is used to get the CSI information.

This chapter explores the information that we get from the CSI packets and its relevance to our experiments. Since we are using 3rd party software for CSI information which is mainly designed for the purpose of research, a cross examination on the information provided seems necessary. A sample of CSI packet could be seen in Figure 3.1. Each packet contains the following information: time stamp, number

Field	Value
timestamp_low	386728903
bfee_count	2226
Nrx	3
Ntx	2
rssi_a	39
rssi_b	40
rssi_c	26
noise	-87
agc	24
perm	[2,1,3]
rate	8463
csi	*2x3x30 complex double*

Figure 3.1: A sample CSI packet

of antennas for transmission and reception, CSI packet count, RSSI for receiving antennas, order of antenna permutation, AGC, noise, rate of data transmission, and the CSI complex data. This chapter particularly studies the timestamps, packet delivery and CSI value information. For experiments is it also important to have control over the wifi properties. Thus the kernel file used for accessing attributes like data rate, bandwidth, guard interval etc are also part of the study.

3.1 Setting the WiFi attributes

In a Linux system, `debugfs` is a file system in the kernel which provides information to the user space and is used for debugging purpose. When a system is connected to 802.11 connection, a directory is created in the `debugfs` along with the stations Media Access Control (MAC) address. Rate_n_flags is one of the entry in this directory which stores the information about the rate of transmission like active transmit antennas, the data rate, modulation technique and so on. The values in this table could be read and edited to set the required data rates, number of transmit antennas and selection between bandwidth of 40MHz and 20 MHz using the rate_n_flags bit fields. The bit fields could be summarized in Table B.1.

Table 3.1: Rate_n_flag bit fields

19	18	17	16	15
x	x	x	ant_C	ant_B
14	13	12	11	10
ant_A	short_guard_flag	dup_data	ch_40/20_flag	green_field_preamble
9	8	7	6	5
x	HT_flag	x	x	HT40_dup
4	3	2	1	0
stream_1	stream_0	rate_bit2	rate_bit1	rate_bit0

We could set a data rate of 6mbps to 60 mbps when in high throughput mode, 6 to 54 mbps when in legacy OFDM mode and 1 to 11mbps when in legacy CCK mode using the bits 2:0. These modes could be chosen using bits 9 and 8. The table also provides an option to choose between short guard interval of 0.4μsec or a normal guard interval of 0.8μsec. Bits 16, 15, 14, 4 and 3 give details on the transmit antennas. Details on how to use this table is provided in Appendix B.

3.2 Time parameter

CSI packets contains a time information which represents the count of lower 32 bits of the 1MHz internal crystal clock of the Intel 5300 NIC chip. Thus it is expected to have a resolution of 1μsec and count up to every 4300 sec or 72 min after which it resets. In this section we study the reliability of the time information in the packets. To verify this property, we ping the AP while tracing CSI with an interval of 0.001 sec for 1 sec and analyze time interval between the first and the last packet. This process is repeated 100 times for better experimental analysis. The time taken to run the script was also noted down as system time and used as the reference for comparing. Figure 3.2 represents the time information in the CSI packets and the system time over 100 trials.

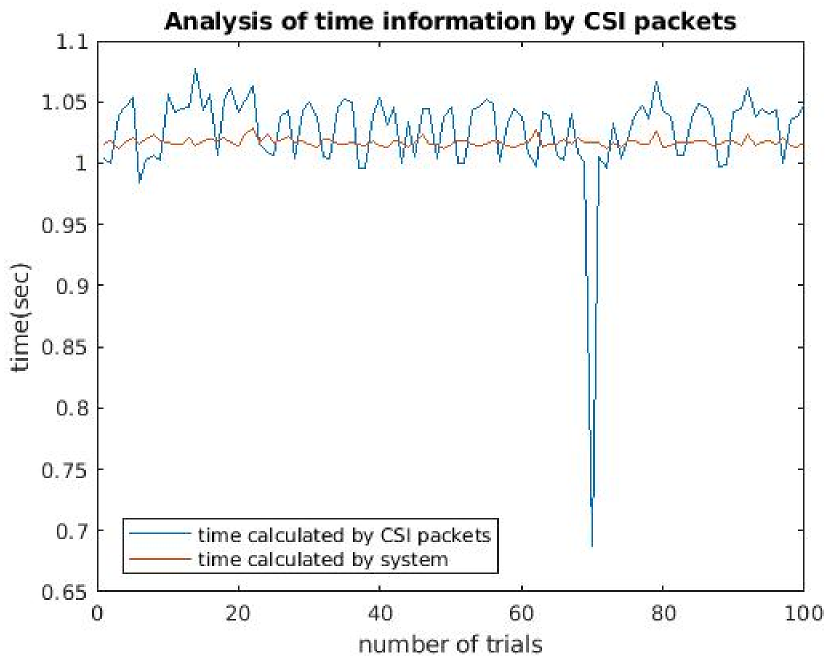


Figure 3.2: Analysis of time information by CSI packets

The mean of system time is 1.0172 sec whereas the CSI packet time is 1.0263 sec which seems to be reasonable. But the standard deviation of system time is 3.2 msec whereas for CSI packet time is 40.4 msec. Thus we can expect the experimental time information to be correct to the order of a few msec. Although, we expected the time information to be precise up to the order of a few μsec which is not achieved, but the precision of a few milliseconds is fair enough for our experiments. The value also drops abruptly for one instance to about 0.68 sec which infers that the system should not be dependent on this information in case of time critical activity recognition applications.

3.3 Packet delivery

When connected to a WiFi connection usually there is no control over the packet delivery rate as it is directly controlled by the usage of the Internet. But for activity detection it is necessary to make sure to have enough sampling rate corresponding to the speed of activity. To maintain a particular sampling rate for experiments, we ping the AP with a specified rate and expect to get the same. In this section we study the reliability of packet delivery. To verify this property, we ping the AP with an interval of 0.001 sec and 0.01 sec for 1 sec for two different experiments and analyze the number of packets of CSI arrived. The process is repeated 100 times for experimental purposes. Figure 3.3 shows the actual number of packets arrived in each second and expected packets as 1000/100 over 100 trials. It also shows the packet delivery when no ping was made.

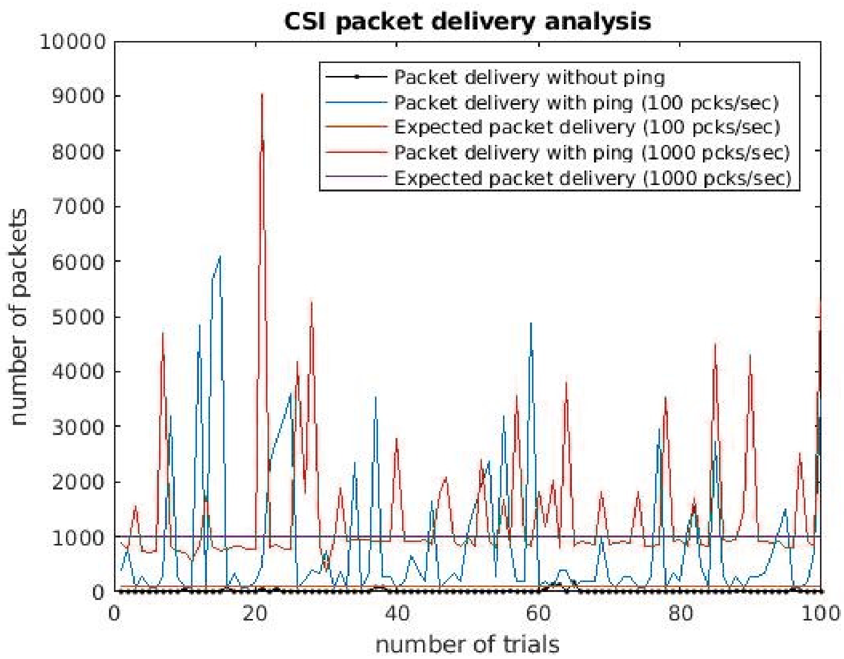


Figure 3.3: Packet delivery analysis

The packet delivery rate when there is no ping is very low with 85% of the values being zero and maximum packets of about 173 at trial number 65. When pinged at a frequency of 100 Hz, packet delivery rate is always above 83 with a mean of 882 packets and maximum value reaching 6080. When pinged at 1KHz frequency the minimum of experimental packet delivery rate is 363 at trial number 30, maximum of 9012 at trial number 21 and the mean of 1417 packets. The packet delivery rate in case of pinging is reliable in the sense that it is usually above the expected rate but not guaranteed. Pinging the AP could be used for our experiments to gain control over the sampling rate as it gives at least 80% of expected rate for more than 85% trials in both the experiments.

3.4 CSI value

For our project, CSI value is the most concerning value as it contains most of the information. Each value in the packet consisted of CSI information in the form of complex values in a matrix of the order $T_x \times R_x \times 30$. To study the reliability and stability of this information we perform two tests one for the short term behavior and other for the long term. For the first test, we perform short experiments one after the other with similar experimental setup during different times of the day and observe the stability. For the second test, CSI value is continuously traced over two days i.e. one working and one non-working day. For the working day we expect to see the amount of variations in the data and for the non working day we expect to see the stability of data in practical conditions.

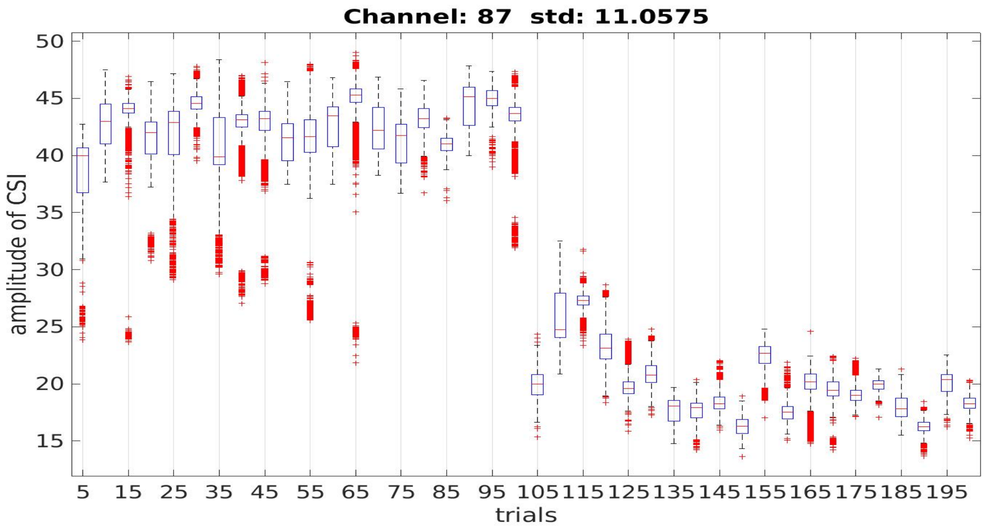
3.4.1 Profiling CSI for short duration

For short time CSI profiling experiments were performed where a person had to remain in standing position at a given point and orientation facing the receiver. It was repeated 200 times at two different times of the day. For each trial, the person had to turn on the CSI logging process, stand at the given position and then turned it off after a few (approx 5-10) seconds. All the experiments were performed when there was possibly no one working in the office to avoid disturbances by external factors. The first 100 trials were performed at 7am and the next 100 trials were performed after 8pm.

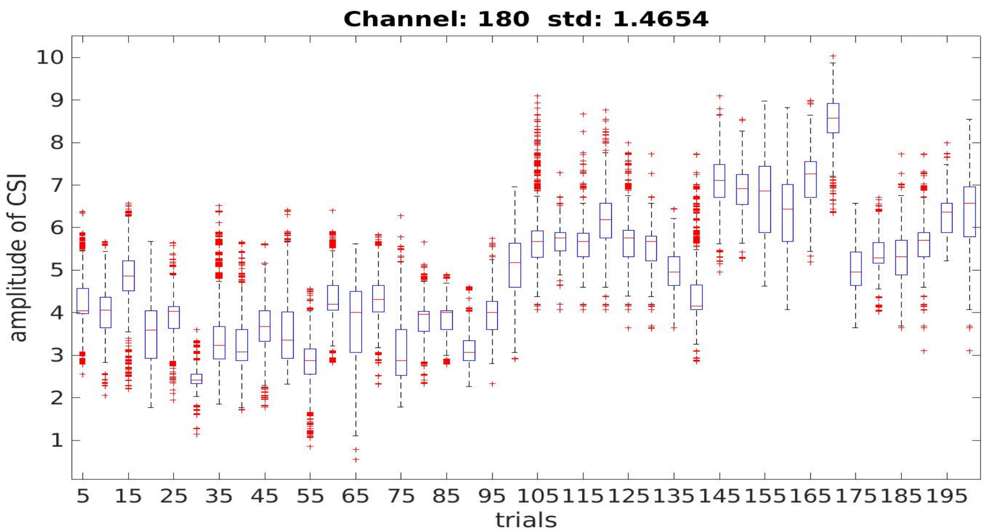
Results and discussion

The amplitude values for each trial were plotted as box plots to observe the behavior. Since there are 180 channels in total and we cannot study them all individually, we only plot a few and study them. For convenience we chose channel with maximum standard deviation (channel 87) and channel with minimum standard deviation (channel 180). The amplitude values of these two channels for all the trials individually can be observed in the Figure 3.4.

The standard deviations of channel 87 and 180 are 11.05 and 1.46 which are maximum and minimum among all channels respectively. It is observed that for each consecutive trial the amplitude varies by about 5 value. This could be expected because of a slight change of position or orientation of the person or due to



(a) Channel with maximum standard deviation



(b) Channel with minimum standard deviation

Figure 3.4: CSI amplitude for 200 trials of experimental data

AGC caused by the device. Further study of AGC is discussed in detail in Section 3.5. It is also observed that Figure 3.4a shows is a clear distinction in the values of experiments carried out in the morning and in the evening i.e between trials 1-100 and 101-200. The expected reasons may be environmental changes like temperature, furniture positions across the separation wall of the room or other wireless equipments within the range of WiFi. To study the behavior of CSI over such environmental conditions we observe it for longer duration in Section 3.4.2.

3.4.2 Profiling CSI for long duration

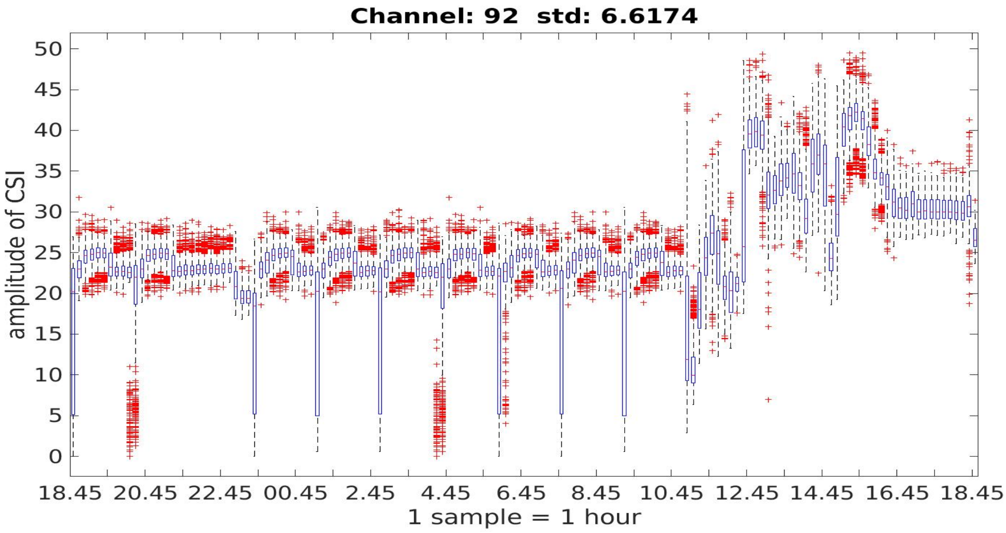
Since we could not get to a definitive conclusion of the reasons that could affect the amplitudes of the CSI during different times of the day in the previous section, we experimenting on tracing the CSI continuously for 24 hours during a working and a non working day. To trace the behavior of CSI signals in case of no disturbance we traced the signals on a non working day for and then plot it using box plots. To compare this with real time scenarios, we also traced the CSI on a working day. It should also be noted that the separation doors were closed during the non-working day, whereas open and in use during the working day.

Results and discussion

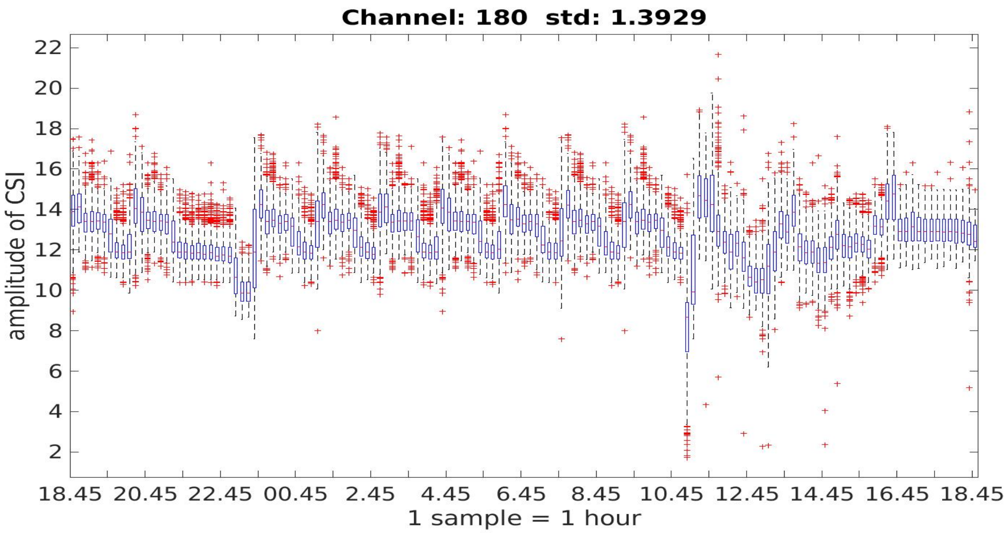
Both the data were taken with a sampling rate of 10Hz. This was later down-sampled up to 2 hearts to have a clear plot. In the box plot, each box contains data for 10 min(about 1200 samples). Thus we have almost 144 box plots for 24 hours. Similar to the section 3.4.1 we plot only the channels with maximum and minimum standard deviation. For working day, CSI was traced from 18.45 on 28^{th} June (Thursday) to 19.15 on 29^{th} June (Friday) and Figure 3.5 displays the channels with maximum and minimum standard deviation for this duration. For non-working day CSI was traced from 19.15 on 29^{th} June (Friday) till 19:30 on $30th$ June (Saturday). The Figure 3.6 displays the channels with maximum and minimum standard deviation during this period.

Data on non working day seems to be more stable than the working day. Both days show fluctuations. But fluctuations in the data of working day are more frequent than that of the non-working day. This could be because the doors were open during working day and so the external factors have more influence. It is interesting to observe a high amount of variation in the plot of working day between 11-5pm, which is the time when people use the room for microwave or coffee machine. In the Figure 3.5a, after 5pm the data is observed to settle down to a new value probably due to the new positions of furniture after use.

The reasons for the periodic disturbances even during the night around 2am or 4am may be because of multiple reasons like regularization of refrigerator or coffee machine close to the experimentation room or due to presence of a person though unlikely. These are just hypothesis and for a definite reason these machines need to be closely monitored which is out of the scope for this project.



(a) Channel with maximum standard deviation



(b) Channel with minimum standard deviation

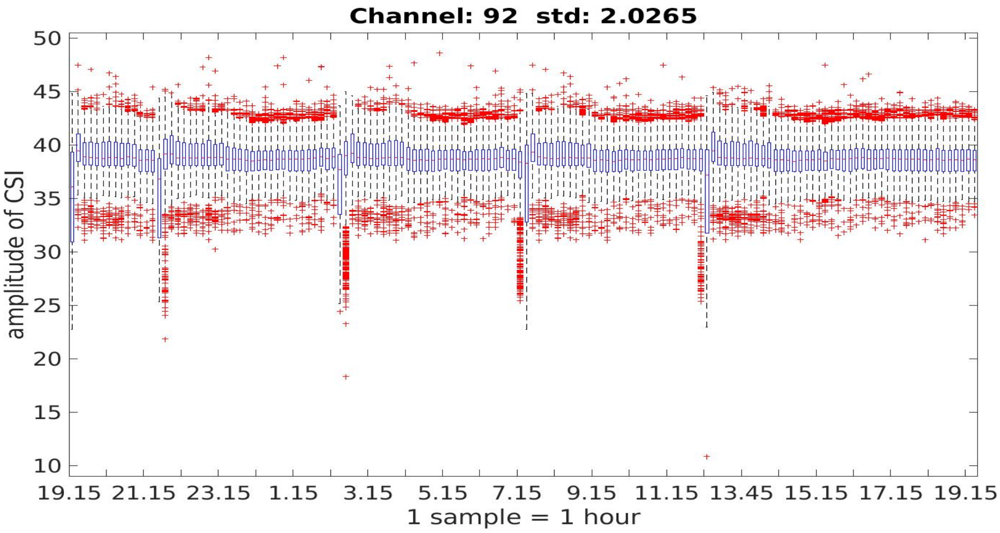
Figure 3.5: CSI value profiling for working day

3.5 Effect of AGC

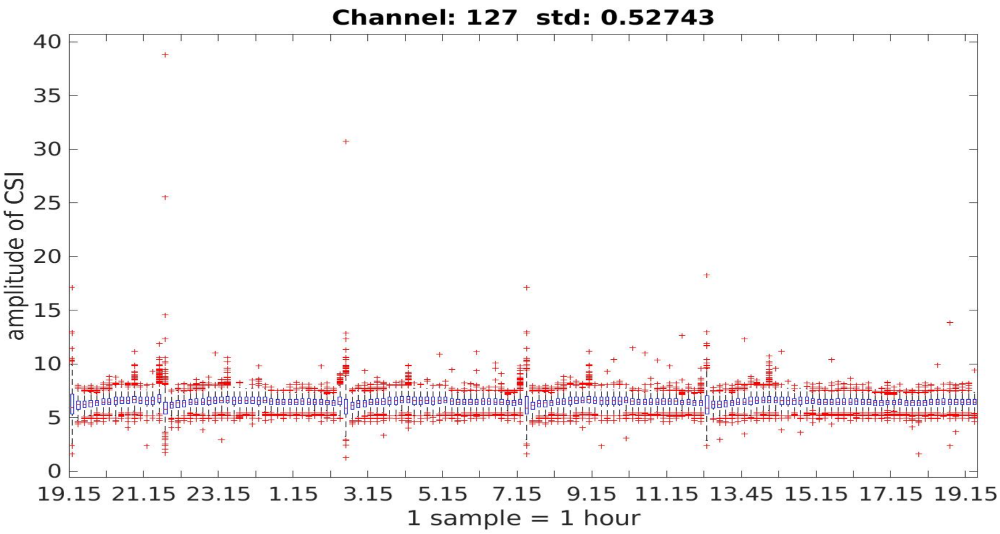
To analyze the effect of AGC on the CSI values we set up an experiment where there is no subject in the room and all the furnitures remain still. We trace the CSI for 5 sec each trial. And repeat these trials one after the other 50 times.

3.5.1 Results and Discussion

The traced CSI values give us the values with NIC's internal reference value. In order to get the absolute CSI value, it is scaled with respect to RSSI and noise. The resulted CSI is the channel matrix H which is expected to be adjusted to the



(a) Channel with maximum standard deviation

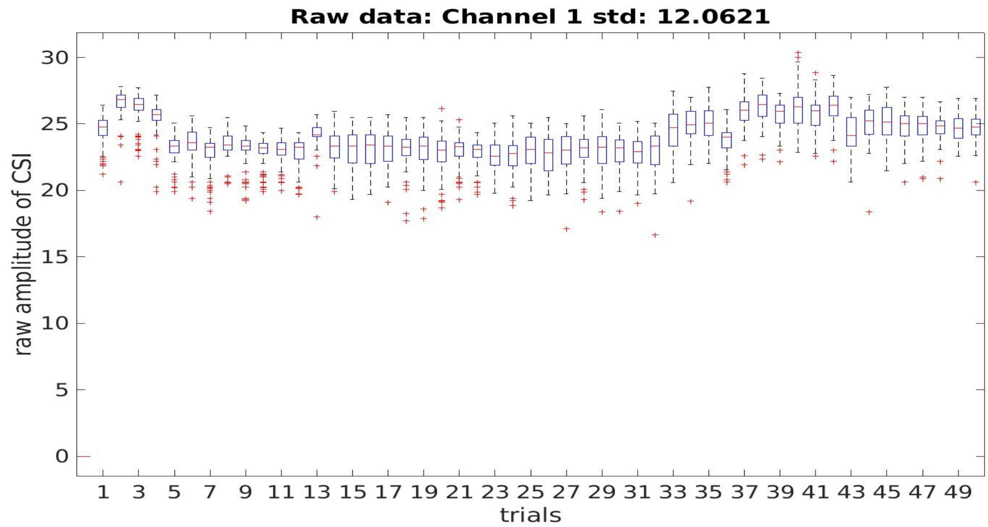


(b) Channel with minimum standard deviation

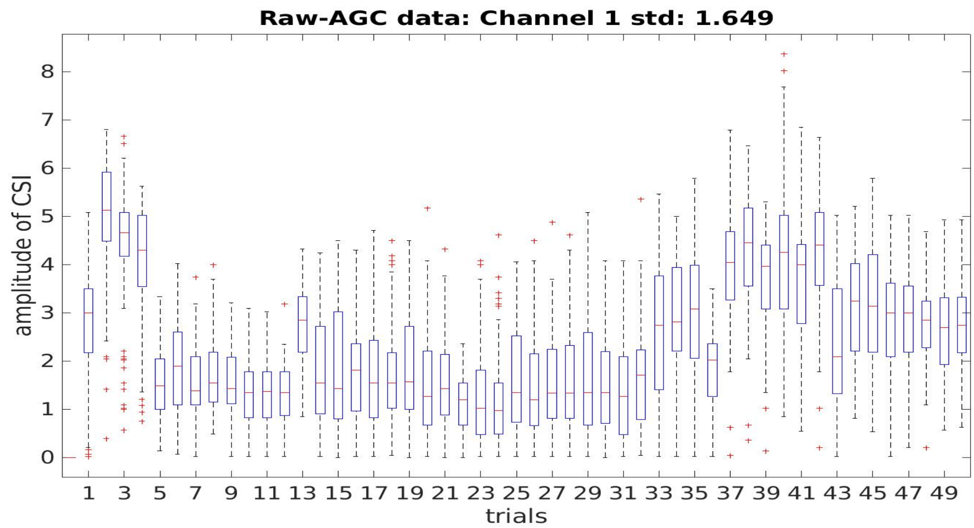
Figure 3.6: CSI value profiling for non-working day

environmental conditions. We study the effects of AGC for both the values of CSI, the one with internal reference referred as 'raw value' and the scaled one referred as 'scaled value'. We subtract AGC value provided in each packet from these values and observe their behavior. Figures 3.7 and 3.8 show the effect of AGC on raw and scaled values of CSI respectively.

The values for raw data vary between 20 to 30 and for scaled data between 12 to 16. Whereas after removing the AGC the raw data varies between 0 to 8 and the scaled data varies between 5 to 40. For raw data, the range of values are just scaled down from 25 to 4 but still vary in the similar fashion. Whereas in case of scaled data, after removing AGC values, the values spread out evenly on a larger



(a) Raw amplitude data for CSI



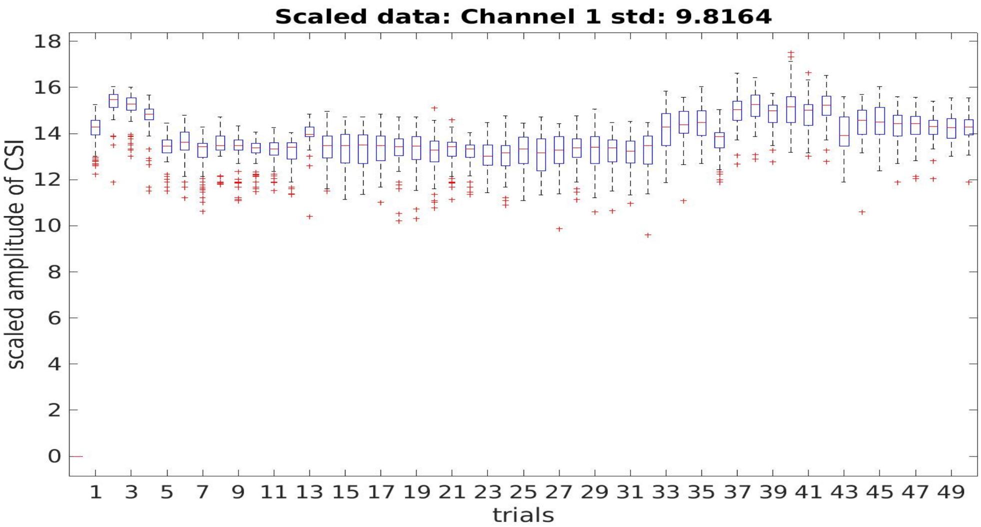
(b) Effect of AGC on raw amplitude data

Figure 3.7: Effect of AGC on CSI raw amplitude data

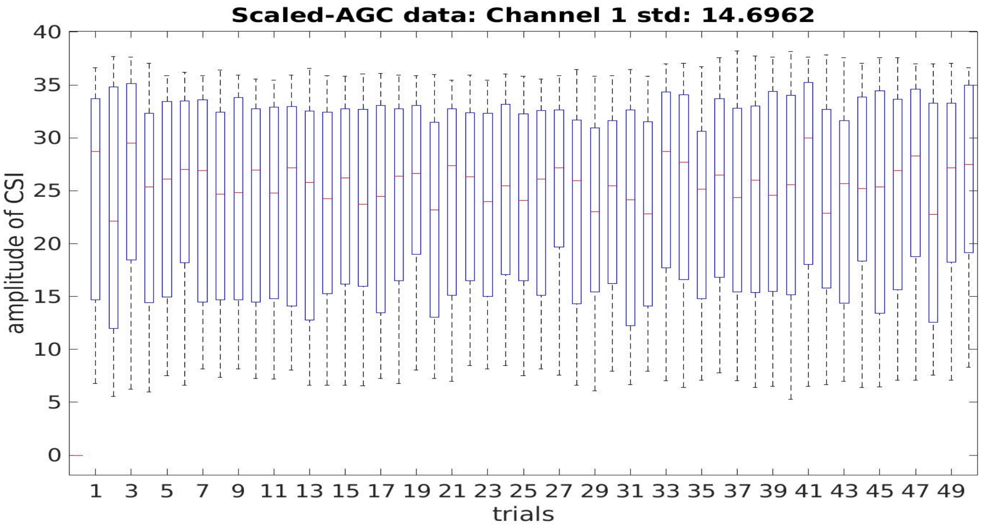
range. Removing AGC from scaled data gives more stable result than compared to raw data.

3.6 Summary

In this chapter we studied a few parameters of the CSI packets relevant to this project. The first one, time stamp, expected to be accurate up to a few micrometers was found to be precise up to 50msec. Although it was not as precise as expected, it is still suitable for our experiments. The packet delivery without pinging is observed to be very low and not reliable and pinging the AP provides a means



(a) Scaled amplitude data for CSI



(b) Effect of AGC on scaled amplitude data

Figure 3.8: Effect of AGC on CSI scaled amplitude data

for reliable packet delivery. When profiled for short duration, each time the system starts logging data, AGC causes fluctuations in the CSI amplitude data. This could be compensated by profiling the scaled data with respect to AGC. Whereas, when profiled for longer duration, the values are more stable with periodic fluctuations. The cause for fluctuations in CSI amplitudes is unknown due to a number of possible factors.

Chapter 4

Experimental analysis

Once we have the understanding of CSI packets, we use them to identify activities performed by people. This chapter covers details of the experiments performed in this project starting from dynamic activity recognition to static posture recognition. The basic idea behind dynamic activity recognition is that they have information as series of CSI log over time whereas static postures are recognized as a single CSI value for a particular time instant. In this chapter first we explain the experimental setup used for the experiments and then explain the experiments in detail. We start with a very simple experiment which detects presence of a moving person inside the room. Then we move on to another dynamic activity recognition system where we detect basic shapes made in the air by a finger tip. And at the end we discuss the static postures recognition of a person at a given time instant by observing the CSI value of that instant. Each system is tested for credibility of the features and reliability of the system. For any given system it is important to find out the features which are informative and provide good accuracies for classification. Since WiFi CSI data is unstructured and still naive in this domain, it is also important to test if the same system is reliable and could be used in future.

4.1 Experimental Setup

Figure 4.1 shows the setup of the room used for the experiments. It is a usual office room consisting of a cupboard, table, few chairs and a computer system. Two of the chairs were used to place the transmitter and the receiver at the same height at the ends of the room. For the experiments, a router with 2 antennas was used as transmitter and Intel 5300 with three antennas was used as a receiver in a PC. The transmitter is placed on the left most chair in the Image 4.1 and the receiver on the right most chair. Both the components were kept at a height of 0.75m from the ground at about 4m apart from each other. 3rd party drivers [31] were installed on the Linux based computer which used 802.11n Wi-Fi protocol. The driver provided CSI packets of 393 bytes each. The sampling rate could be controlled from by pinging to the AP at given intervals. Experiments were done using 48mbps speed with 64 QAM modulating technique. Due to using these drivers, the dimensionality of the received CSI data was limited to $N_r \times N_t \times 30$ since the drivers grouped the individual sub-carrier information into 30 channels. The traced CSI data was written to a `.dat` file. Matlab R2017B was used to read the data from `.dat` file and analyze it.

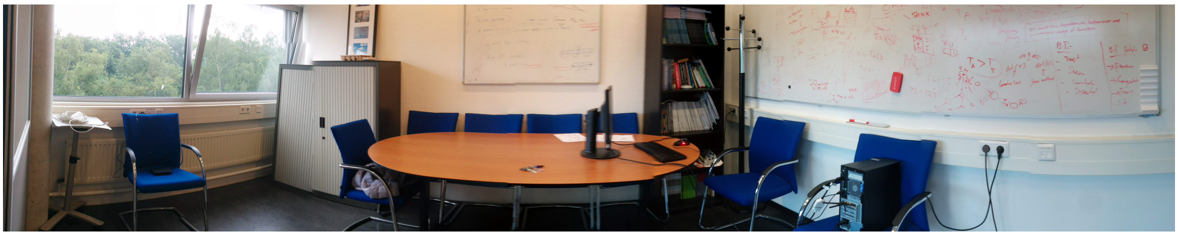


Figure 4.1: Office room experimental setup

4.2 Detect a moving person

Before going to a complex application we build a very simple application which detects the presence of a moving person. The use cases for such a system could be an intrusion detection system or controlling smart appliances. This simple activity detection system was done for validation purpose and to test if such a system could be used for real time detections. We first train and test the system with the data saved in the system which is also referred to as offline system. Later, on a different day we also test the system on real time. Thus, this would also provide a reliability test for the system which determines if the system could be used on any other day in general. While working as a real time activity detection, the system was recorded and the video was used for demonstration purpose. This could be found at video link [1].

4.2.1 Offline system

This experiment is performed in the room as explained in Section 4.1. There were 2 types of classes, used for classification one corresponding to moving and other for not moving. For moving class the subject freely walks in the room and for the

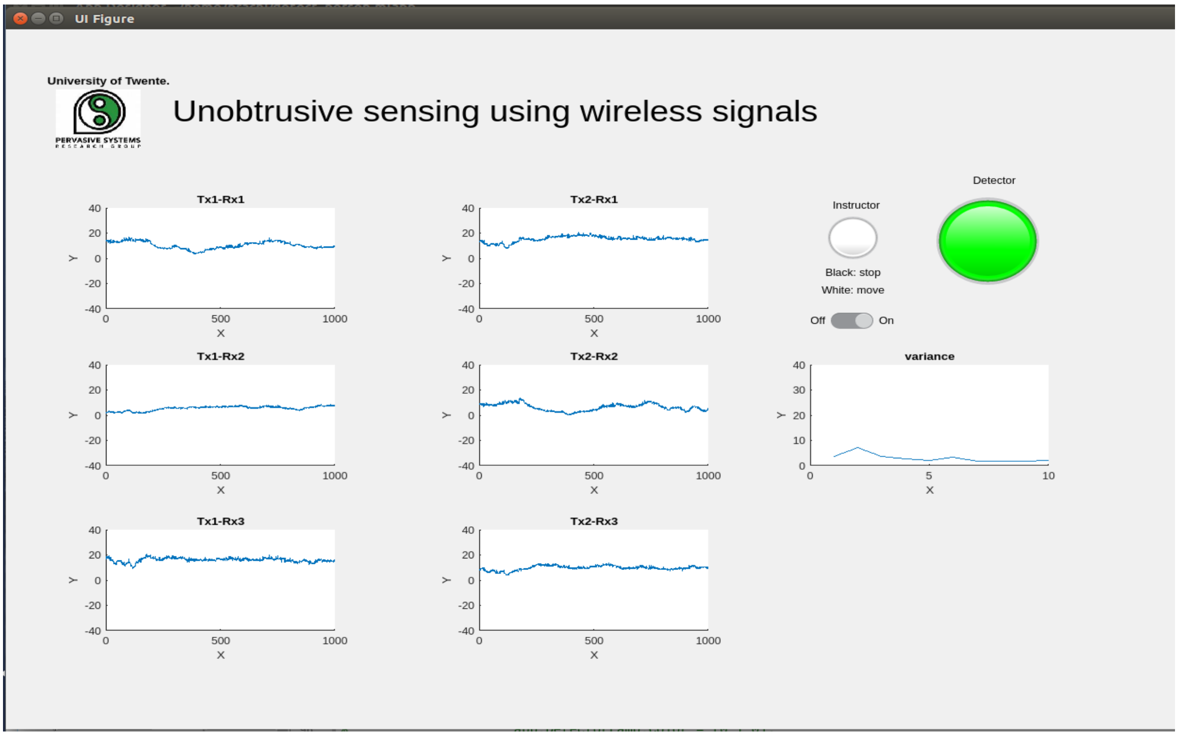
[1] video link: https://drive.google.com/open?id=1eH3VZ3Et4mK-fR3OT1iXhBlqmfvHILp-

other class he is present in the room but does not move. For collecting the data, the experiment were conducted 4 times which were mostly around 20-35 sec each taken after one another. Each experiment is divided into a time span of 0.5 sec corresponding to approximately one step interval and each and each part is treated as a different activity. In total we had around 132 data sets for stationary class and 150 for moving class. Similar to the [9], variances over all the channels are used as the feature for classification. The data was split in 4 groups wrt its experiment number and each group was cross validated with each other with SVM as the classifier. This gave accuracies between 96-99%. Thus variance was verified to be a credible feature for this application.

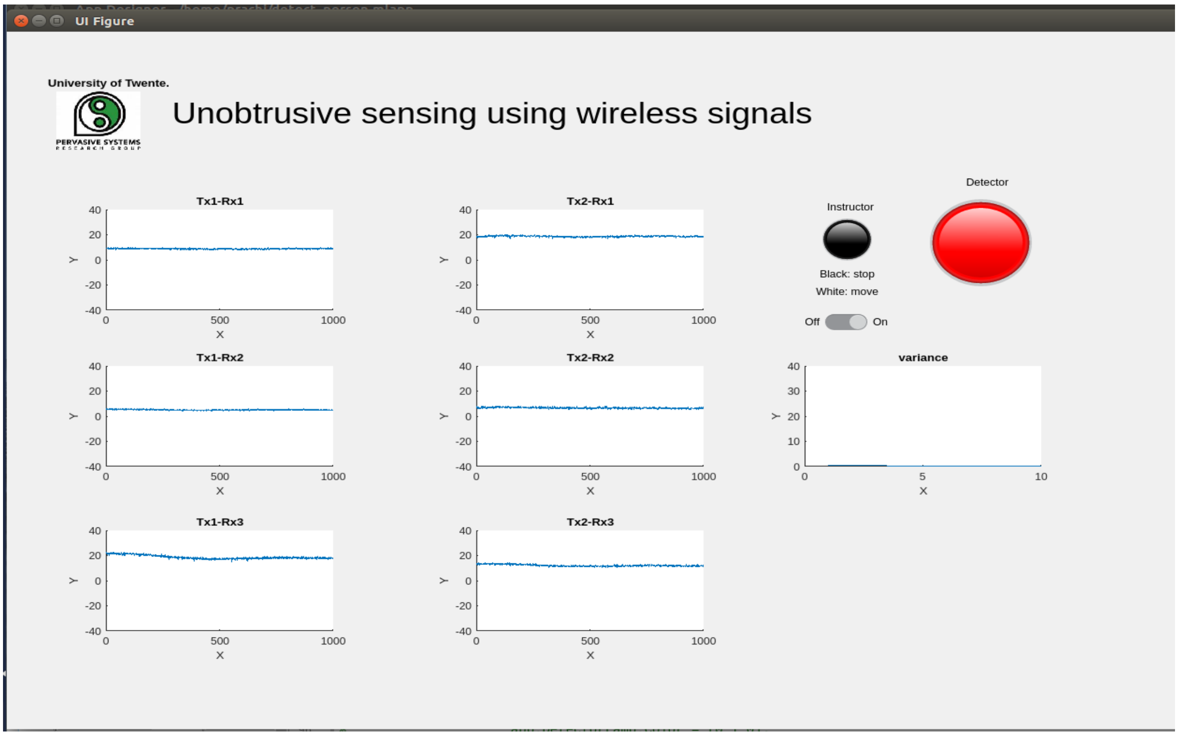
4.2.2 Real time system

We build an applet using the matlab-app which behaves as an GUI for real time detections. Data from all the experiments was put in the SVM model collectively and used for real time detection. For real time validation, the applet displayed whether the subject had to move or stay still. This was used as the ground truth. And the detections were also simultaneously displayed on the screen. Figure figs. 4.2a and 4.2b show the applet when it detects a moving and not-moving person. The signals for the 6 antenna pairs is displayed in the graphs along with the overall variance shown in the graph below the lamps. The small colored lamps are used as the indicator to the subject whether to move or not and the bigger lamps are the detections made by the system. The black color in the indicator is to indicate the subject to stay still and white is to indicate to move. Similarly, the red color of the detector is when it detects the person as not moving and green for not-moving. The ground truth and detected values were later compared to find out the accuracy. We also measure the certainty of prediction made by the classifier.

When tested for 4 min, alternately moving and stopping for 8 sec interval, we performed each activity 15 times each and achieve an accuracy of 86.26% with a mean certainty of 91.24%. Thus the system is a reliable system. But, if we consider the predictions which had a certainty of 70% and above, the accuracy drops down to 68.59%. This means that the system is not very certain on its predictions. These numbers could be improved by increasing the number of data for train and test, including more features or by reducing the dimensionality to the most significant ones. These could be a part of study for future work.



(a) Applet showing the detection as movement



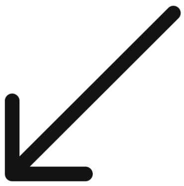
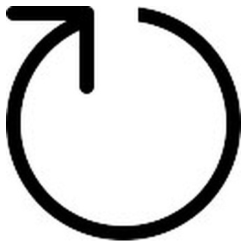
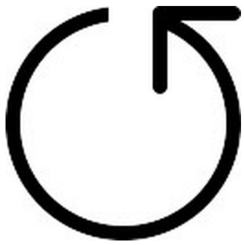
(b) Applet showing the detection as not moving

Figure 4.2: Screen-shots from applet

4.3 Basic shapes recognition

The basic idea behind this project was to have a generalized activity recognition system. This can be done by reducing the main activities to smaller and more generic ones. For example, if we have to develop an activity recognition system to detect what a person is writing, each word is a combination of alphabets and each alphabet could be considered as a combination of a few straight lines and curves. On similar approach this activity recognition also recognizes a few basic shapes which are drawn in the air with a finger tip. The 5 different types of shapes used for experiments are depicted in Table 4.1. The arrows show the direction in which one has to move the finger tip. For example shape 1 is movement of finger tip in a straight line downwards, shape 2 and 3 are diagonal lines and shape 4 and 5 are clockwise and anticlockwise circles.

Table 4.1: Experimental shapes drawn in the air

				
1	2	3	4	5

4.3.1 Experimental details and methodology

For each experiment the subject was standing at a specified position facing towards the receiver and making the shape in the air approximately 60 cm in length by their finger tip. The position of all the furnitures were kept stationary during the experiments. A little extra CSI tracing for a few seconds before and after drawing the shape is done for safe margins before and after the start and end of the informational data. Each experiment is repeated for multiple trials. Steps for feature extraction and classification are mentioned below and also presented in Figure 4.3:

- Noise Reduction: The first preprocessing step is to remove the noisy components from the signal. The removal of noise to give a clean signal is done by taking moving average over the signal. This method takes the average of 100 leading and 100 lagging samples. This corresponds to averaging data of about 200 msec in total.

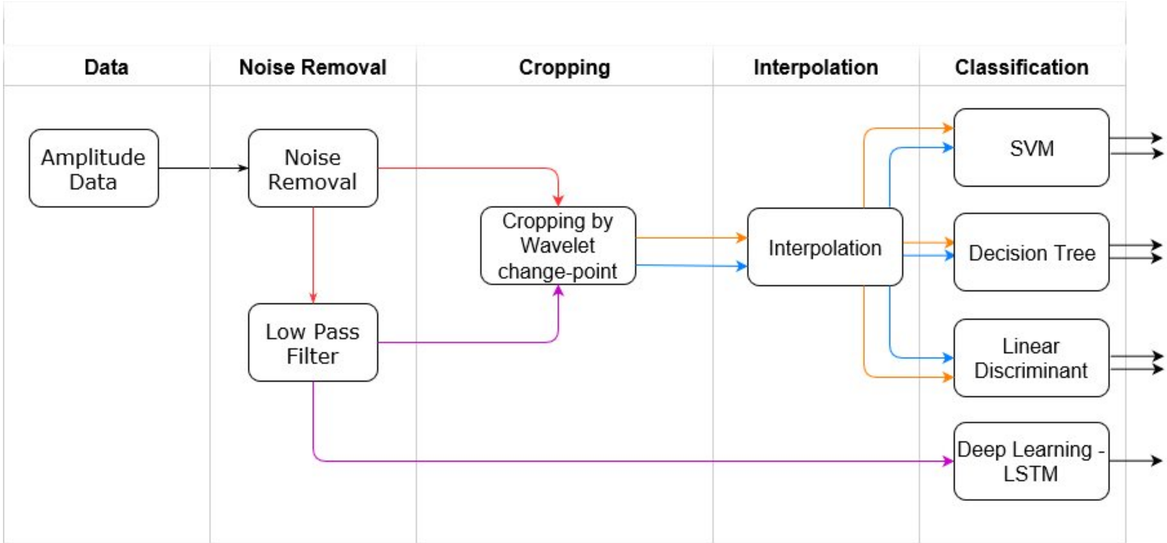


Figure 4.3: Flow Diagram for shapes recognition

- Low-pass filter: In order to extract the information from the signals corresponding to the movement of hand, we take the low pass filter with cut-off frequency 25 Hz. This frequency range is expected to be in the range of hand movement. A 1000 order FIR filter is used for clear cut off and narrow transition band.

- Cropping the signals: The experiments had a few sec of data with no movement before and after the actual action performed. The part of the data where no action is been done is expected to have no change in value over time, whereas the part of action is expected to have some variation. In order to have a common cropping point for data of all channels of the same trial, cropping point of mean of all the channels is calculated and later applied to individual channels. We use maximal overlap discrete wavelet transform and reconstruct the signal over different scales. Then find the change point of the transformed signal with proper scaling. It is experimentally observed that 'haar' wavelet with 5 as the scaling factor corresponds to the information signal.

- Overcoming uneven time interval: Cropping might result into data with uneven time intervals for experiments of different trial numbers. In order to use classifiers we need to have data with same length. For doing so we interpolate all the data to equal number of points.

- Classification: For this experiment there are total 95 trials of data. Data with different trial numbers are separated in 90:10 ratio for each antenna pair. 90% of data is used for training and 10% for testing. SVM, decision tree and linear discriminant are used as the machine learning classifiers. Signals before and after low-pass filtering are the two types of data applied to the classifiers. A deep learning classifier is also used with two LSTM layers with 150 and 80 hidden layers respectively. For deep learning, cropping is not required as it is expected that the classifier is capable of extracting meaningful information. Thus we have 7 different models which are being compared as seen in the Fig 4.3.

4.3.2 Results and Discussion

We first discuss the step by step output of pre-processing. Figure 4.4 shows output of the de-noised signal for a given pair of transmitter and receiver. The figure clearly removes the fluctuations in the signal and the output is a smoother curve. Figure 4.5 shows the signals of 6 different antenna pairs each containing 30 sub carrier signals plotted over time. The information content of each antenna pair is different. Antenna pair 2 and 5 do not have much variance. Whereas antenna pair 1 and 4 vary the most. The signals within an antenna pair show high amount of correlation. The first figure in Figure 4.6 shows the signal after low pass filtering and the second one shows the same signal after being cropped. Filtering removed all the high frequency noise in the signals. In the cropped signal, the initial part of the signal corresponding to no action (frames 1-1500) is being removed but the later part could not be removed. The reason for this may be that even without any movement, the signal varies slightly over time which is close to the information signal. Thus it is difficult to separate the informative part in time domain.

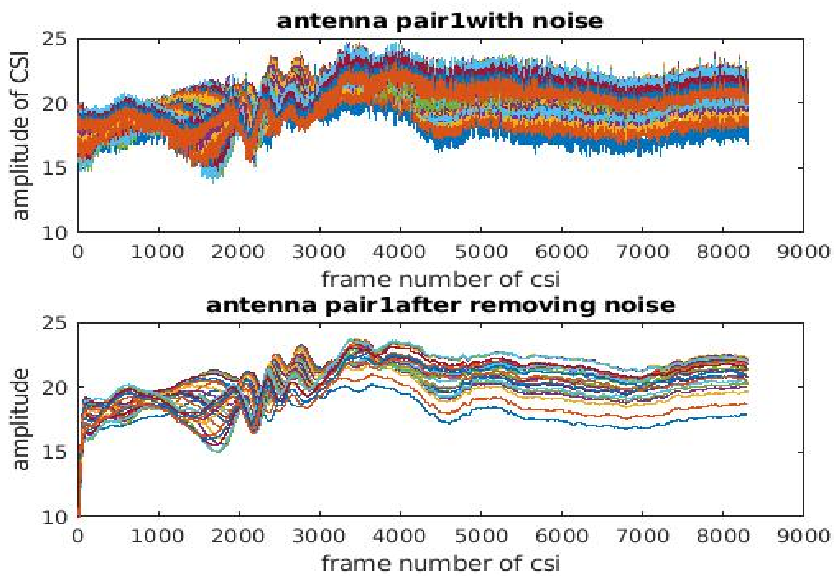


Figure 4.4: De-noising the data by moving average method

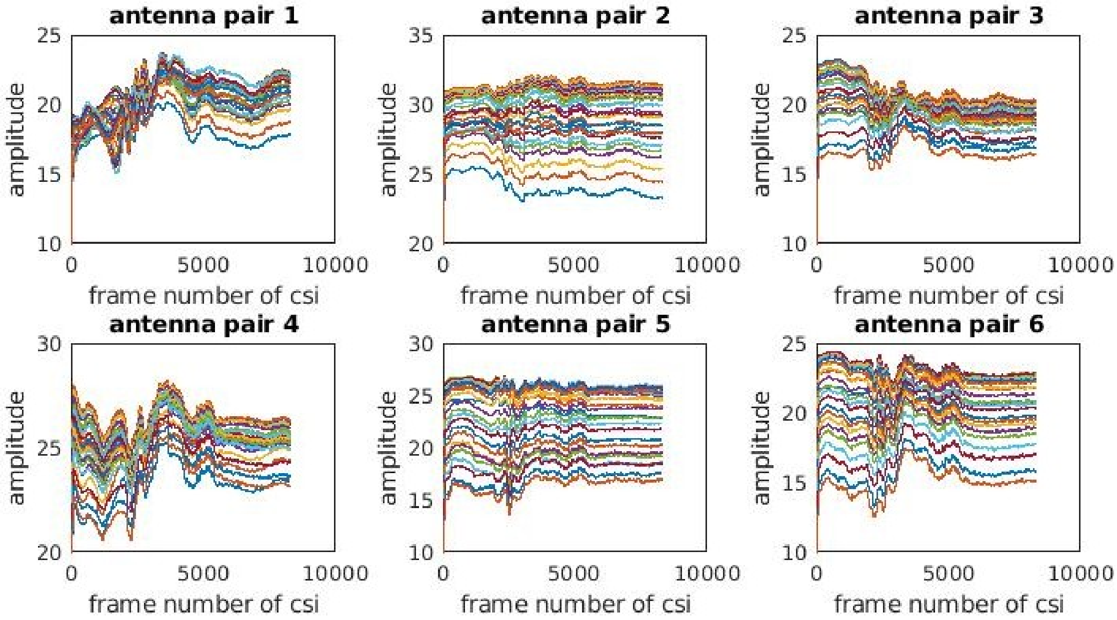


Figure 4.5: Amplitude of CSI data for Tx-Rx pair of antennas

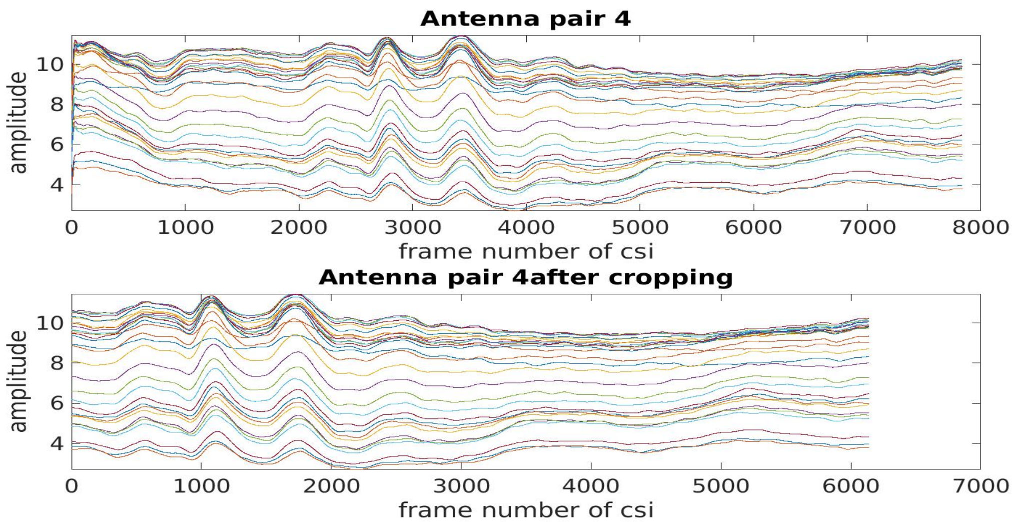


Figure 4.6: Cropping the signals with informative part

Lastly, Fig 4.7 shows the classification accuracies for the seven models for different antenna pairs. The bars in blue represent data before low pass filtering, green is for data after filtering and the red one is the deep learning classifier. The highest classification accuracy obtained is around 60-68% for antenna pair 1 with decision tree classifier and antenna pair 5 with decision tree and deep learning. Antenna pair 1 seems to be the most informative since it has a number of classifiers having accuracies around 50%. Overall, after filtering, classification either remained almost same or improved. Decision tree with data after filtering seems to have better accuracies for all the antennas and even competes with the deep learning. Deep learning with two LSTM layer does not add much to the results even after taking long training time.

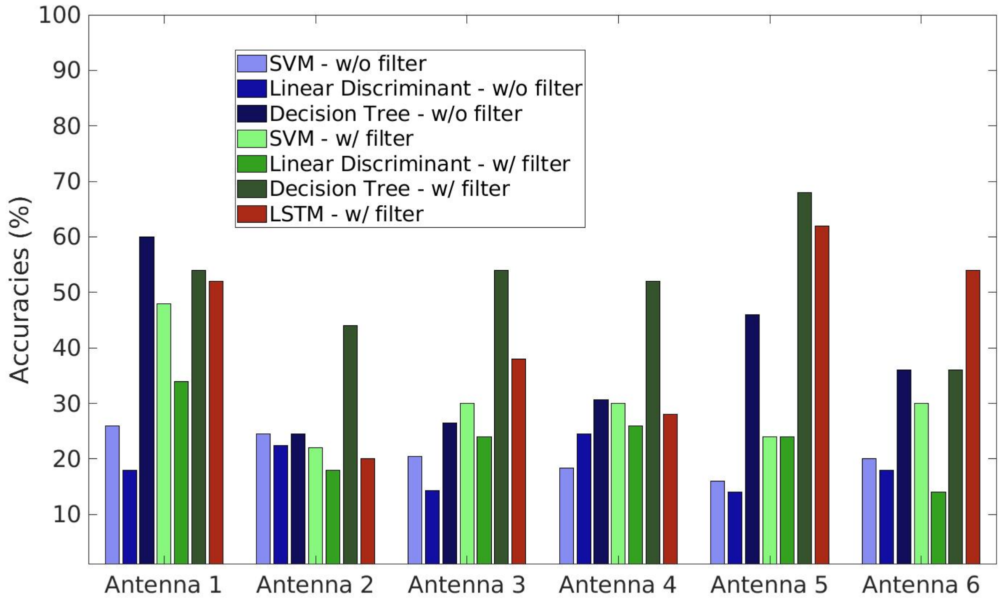


Figure 4.7: Accuracies for classifiers

In case of machine learning techniques, the reason for the low accuracies could be improper cropping. As observed in Fig 4.6, the low frequency noise signals are not easy to separate from the information signal. Feature extraction form time domain signals seems difficult even with the deep learning mechanism. Thus either a mechanism for proper cropping could be implied or the features in the frequency domain could be explored. Since the selected features do not provide good accuracies, the system is not tested for reliability.

4.4 Static postures

This section explains the activity recognition for static postures. Static postures means that we try to detect a posture at a given time instant. Thus a single CSI value is considered as the information for that particular instant. For experimental purpose a few basic postures of exercises are selected with different hand and leg positions. The selected postures are depicted in Figure 4.8. This project is limited to single subject scenario. Given a stationary experimental setup, we expect the WiFi signals to behave in similar way for a given posture. It is expected that the environmental factors would also play a role in such a system. To analyze the effects of such factors the experiment are performed in a controlled and an uncontrolled environment.

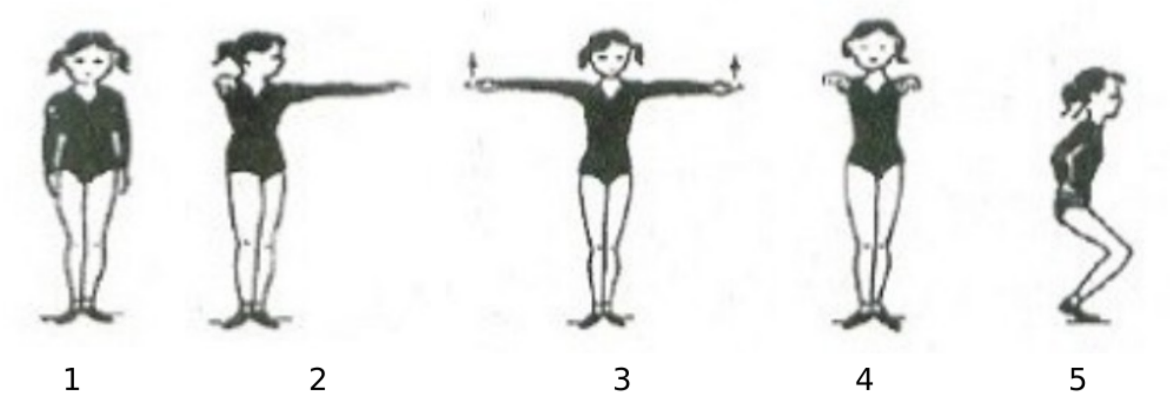


Figure 4.8: Static exercise postures for experiments

4.4.1 Experimental details

For static posture detections, the experiments are performed at two locations. One, in the office room setup as discussed in Section 4.1 and other in an anechoic chamber. An office room is an example of practical environmental conditions which we use in day to day life. Whereas anechoic chamber provides ideal environmental conditions since the walls, ceiling and floor are designed to absorb the radio waves. The anechoic chamber used for this project is a 3m semi-anechoic chamber [32].

The experiments in the anechoic chamber also used the same devices as in the office room. The setup in the chamber consisted of only the transmitter and receiver antennas placed at a distance of about 3m. The computer was placed outside the chamber for doing the analysis. The receiver was placed on a stand made of PVC material and the router was placed on the ground at the diagonal corners of the room. Thus the effect of CSI signals was limited to the system setup and the subject. Figure 4.9 shows the setup inside the chamber.

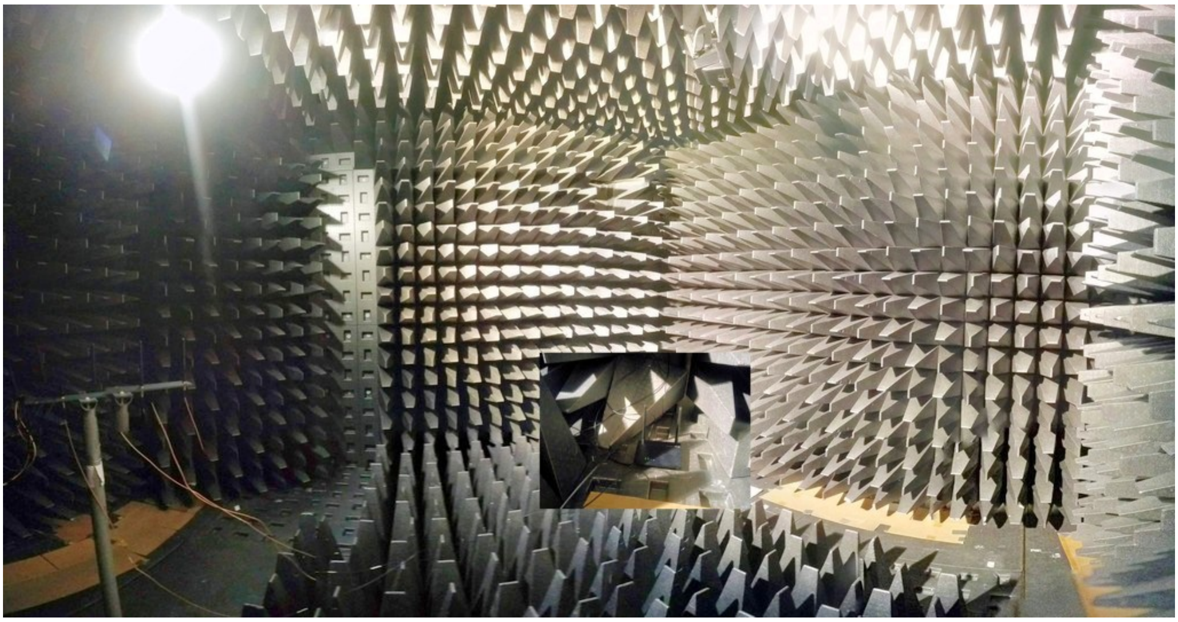


Figure 4.9: Anechoic room experimental setup

For both the setup, each experiment consisted of a stationary experimental setup where the subject had to perform the activities at a given position with fixed orientation facing the receiver. For each trial, subject had to start CSI logging, perform the experiment and stop it after a few seconds. Thus a single trial could be considered as a continuous activity of the same posture. And each CSI log contains data for a single time instant for that posture.

4.4.2 Methodology

For a given static posture, there are number of trials being performed within a day. Firstly, we expect the data within the same trial to be consistent and also expect to reproduce the same over other trials. For this, we do the data stability test and find out the features over different trials. Once we have a system with credible features, we test the system for its reliability over number of days.

1. Data stability Analysis: Considering each CSI log to be an independent data for that particular time instant, we classify the data by mixing all the trials. This is a primary test to verify the stability of data. Hence this test is done only for amplitude of CSI.

2. Significance of features: The next step is to verify if the data taken for different trials remain consistent over time. For this the classification is done by separating the data with respect to trials. The features considered for classification

are amplitude, phase, AGC profiled data and zero mean data. From Section 3.5 we know that AGC affects the amplitudes. Thus AGC profiled data is calculated by removing the AGC from the scaled amplitude. Since the data is not expected to vary with respect to time, we expect the information to be contained in the relative values of channels. Thus we calculate zero mean data to bring the values to a common reference. This is obtained by removing the mean of all the channel data for a given CSI log. For experiments performed in anechoic chamber we also consider the normal profiled data. Normal profile is nothing but data taken with no subject inside the room and then subtracting it from the experimental data.

3. System Reliability Analysis: To analyze the overall reliability of the system, data taken on different days is cross validated. For this step only the prominent features obtained from the results of the previous step are considered.

4.4.3 Results and Discussion

This section discusses the results obtained for stability of data, significance of features and system reliability. First the results for experiments performed in an office are discussed and then for the anechoic chamber.

Data stability

From the data collected, it was verified manually that given a list of CSI values for a single trial, the amplitude values for all the channels remained almost constant over the samples. The experiments were performed with a sampling rate of 1KHz with each trial of 5 sec interval. Thus, for 20 trials of data, there were $1000 \times 5 \times 20 = 100,000$ CSI logs for each position. After mixing all this data accuracy for classification performed by SVM classifier was 99%. Thus the values could be said to be stable for a given trial. But, cross validation of data from 5 different trials gave an average accuracy of 15%. This could be explained by the effect of AGC as discussed in Section 3.4.1. To compensate for this effect, we decided to take a lot more trials and continued with trials of small durations rather than longer trials.

Significance of features for experiments performed in office room

For this analysis, experiments were performed on different days at approximately the same time for about 50-100 trials, each trial for about 5sec duration. For 5 days data, we trained and tested the data for individual day with 90% train and 10% test data with non overlapping trials. CSI amplitude, phase, AGC profiled data and zero mean data for all the 180 channels were used for feature analysis. The accuracies for SVM classifier could be observed in Figure 4.10

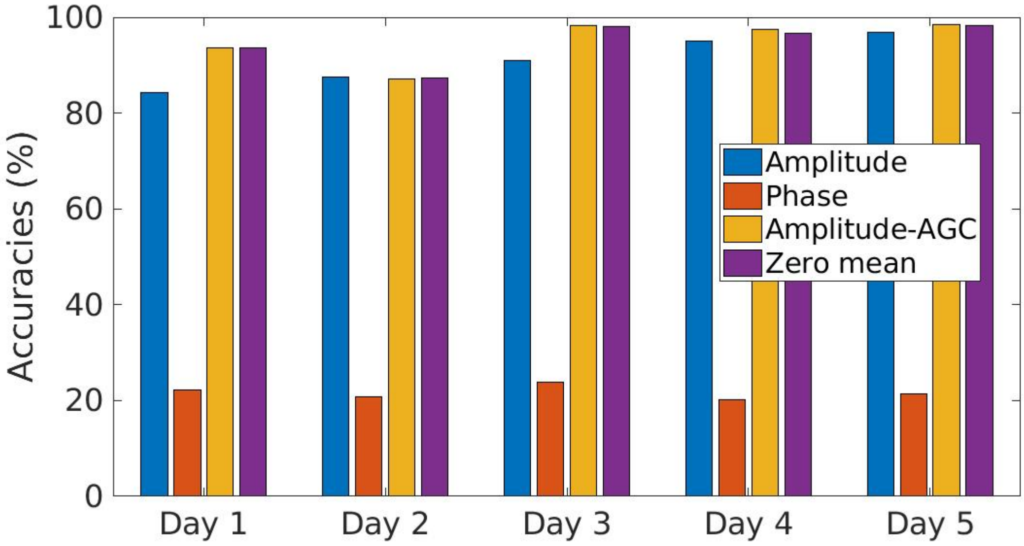


Figure 4.10: Accuracies of individual days

It was observed that all the four features except phase have an accuracy of more than 80% for all the given days. For static postures amplitude data and the profiled data for amplitudes are informative. Whereas phase does not contain information. It is also observed that the AGC profiled data and the zero mean data compensate for the variation in the amplitude over consecutive trials. For having stable system for static posture recognition, 50 trials give promising results for non overlapping trial data.

Reliability for experiments performed in office room

The significance of this test is to verify that the system built on one day could be reliably used on other days. To verify this we cross validate the data for 5 different days with each other. For cross validation we do not use phase of CSI as it is not informative. For 5 days we have total of $5 \times 4 = 20$ validations. Figure 4.11 plots the probability of validations vs accuracies achieved for each feature. Details on individual cross validation could be found in Appendix C.

From the results it is observed that none of the data features could achieve even 50% accuracy. This means that the data from one day could not be used to test the data from other days since the accuracies obtained is very low. The reason behind this could be the movement of furnitures of the room across the walls of experiment

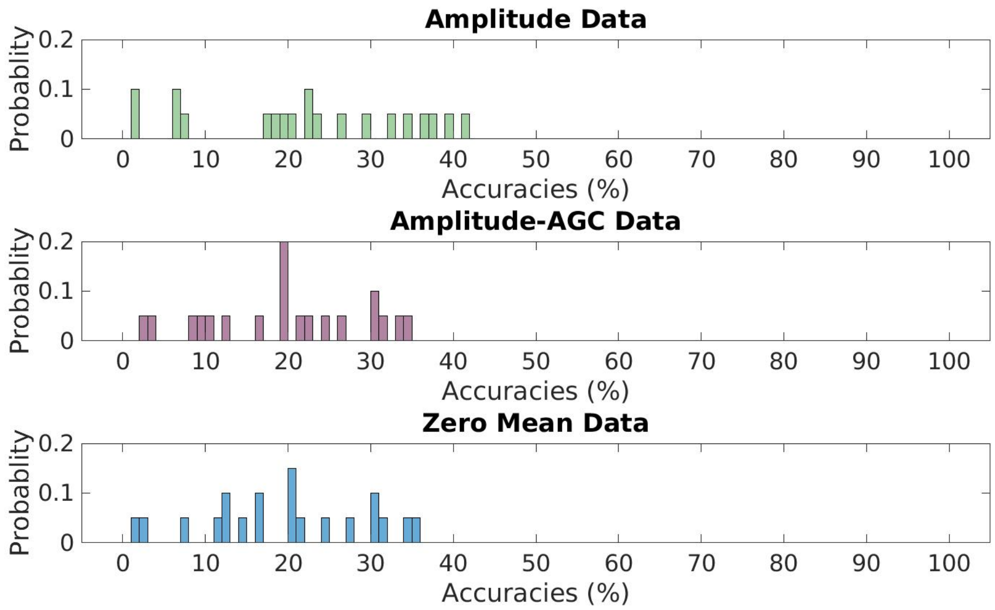


Figure 4.11: Cross validation analysis

room, changes in environmental conditions or due to the offset frequencies within the channel.

For further analysis of such a behavior of CSI signals two different approaches were built up. One was to test the CSI for ideal conditions in an anechoic chamber and other was to perform similar experiments for a few more days inside office room and validate cross validation for data combined for multiple days. Details of experiments on anechoic chamber are presented in the following section.

For the second method of analysis, experiments were continued for five more days and data for multiple days was combined to observe if it could compensate for the environmental effects. Once we had data for 10 days, we combined data of any 5 random days and tested it with another 5 days. Data from day 7, 8, 1, 9, 2 were used in training and days 6, 3, 10, 4, 5 were used in testing which gave an accuracy of 27.61%. This took around 7-8 hours of time. Later 9 days of data was used to train and 1 day of data for testing which took almost two days and had an accuracy of 16.02%. Due to high time consumption the number of cross validations are limited. Also, there was not much of an improvement seen with increasing number of days in the combined data. From data taken on 10 different days it is not possible to build a reliable and reproducible system. It is also observed that we need a high amount of data and a very high computational power in order to continue on this approach which does not seem practical.

Significance of features for experiments performed in anechoic chamber

Figure 4.12 shows the accuracies for system classified by using SVM for individual days. CSI data for normal profiles were only traced from Day3. Thus there is no data available for Day1 and Day2 under normal profiling in Figure 4.12.

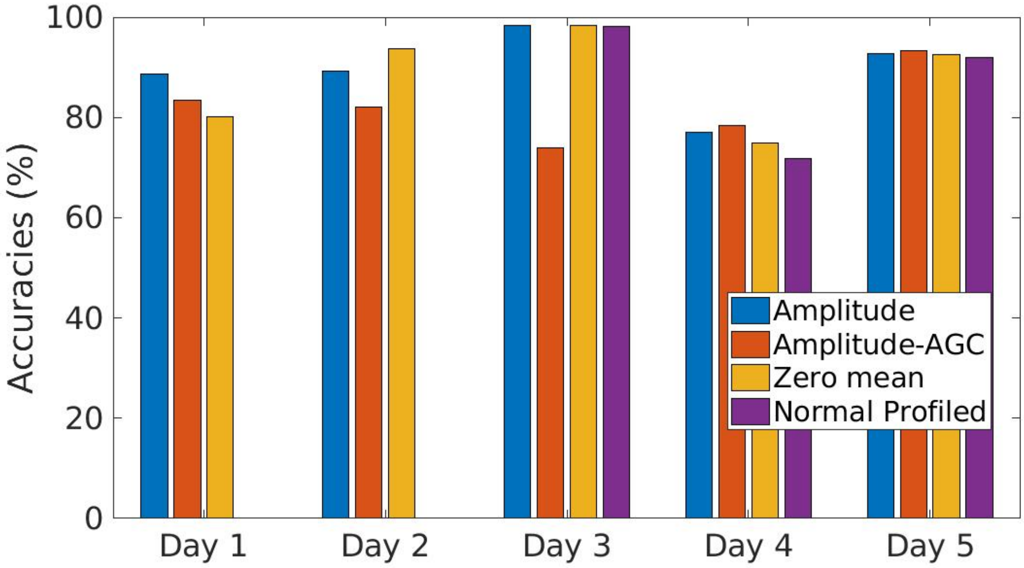


Figure 4.12: Accuracies of individual days

The accuracies for all the days are at least 70% and higher. Particularly for day 4 the accuracies seem to be a bit lower than the other days. There is not much of an effect observed due to profiling on amplitude data. For AGC profiled data, days 1 to 3 show drop in the accuracy and days 4 and 5 do not show significant improvement. Thus, in an anechoic chamber AGC does not seem to play a major role. Zero mean and normal profiling also do not seem to have contribution in such an environmentally controlled room.

Reliability for experiments performed in anechoic chamber

Similar to the experiments in office room, for analysing the reliability in an anechoic chamber, data from different days are cross validated with each other. The four features namely amplitude, AGC profiling, zero mean and normal profiled data are used for cross validation. Figure 4.13 shows the probability of cross validations with respect to accuracies achieved.

It is observed that none of the features could get an accuracy of more than 42%. Thus even inside an anechoic chamber a reliable system for static postures is not

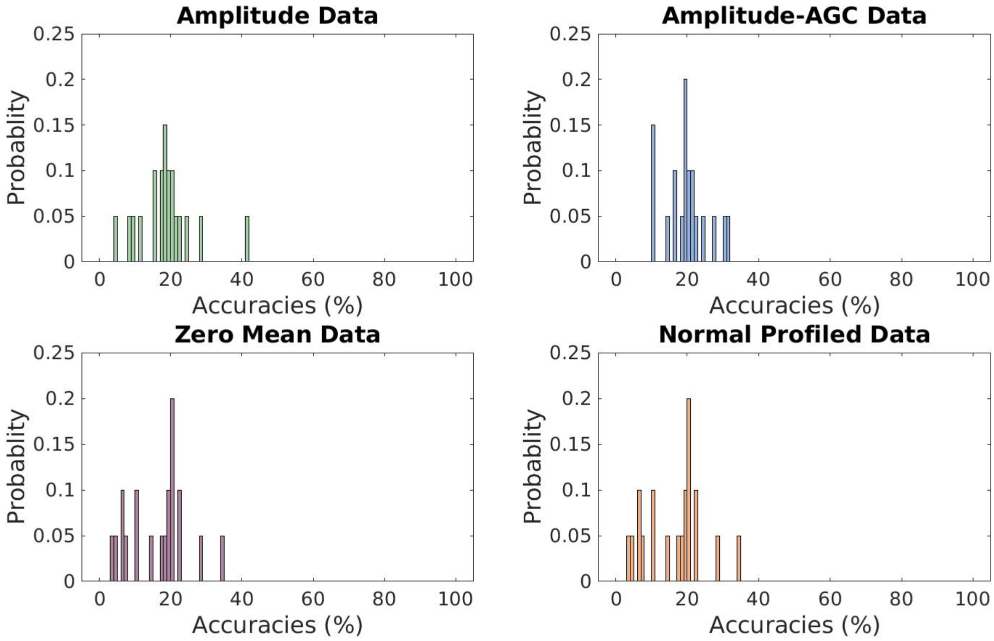


Figure 4.13: Cross validation analysis

possible. From the results achieved so far the fluctuations in the WiFi system like offsets of sub-carriers seem to have a dominant effect than environmental factors.

4.5 Summary

In this chapter we did experiments starting from dynamic activities and then moving to static activities. A very simple activity recognition to detect whether a person is moving or not is observed to be reliable with an accuracy of 86%. Moving to the next dynamic system which detects movement of a finger tip, the accuracy reduces to around 60%. Improvement seems possible for this with improvement in the algorithms and feature selection. And at the end we recognize static postures which were the most significant for this study. Given a stationary environment the system seems to be credible for amplitude data. But it fails the reliability test even for a controlled environment. Thus, the instability in the WiFi system appears to have dominant effects than the environmental factors for a static posture recognition.

Chapter 5

Conclusions and recommendations

This project studied the possibility of an activity recognition system based on static posture detections. It also compared the dynamic activity recognition with static ones. For activities with varying speed, it was easier to classify the data on the basis of simple statistical features. But as we moved towards activities with similar pace, feature extraction and classification became difficult. On the other hand, for static postures, even though the features were limited, they could be classified given that the environmental conditions remained constant. But, due to internal fluctuations in the WiFi system, a reliable system could not be built. It is believed that for dynamic activities, with improvement in features, a reliable system could be built.

5.1 Conclusions

In the introduction three main research questions were mentioned which were addressed in this project. From the work done so far we can derive following conclusions:

1. Can we find a structure for the unstructured Wi-Fi data?

   For dynamic activities, variation in amplitudes with respect to time provides a means of structure of the data . Various statistical measures like peaks, maximum, minimum, variation and standard deviation provide a means to access this structure. But, for static objects structurization becomes difficult as there are number of factors affecting the data. Even when the environmental factors were kept constant the CSI data does not seem to follow a structure. The instability of WiFi system, especially frequency offset is expected to be a reason for instability in the signals for static postures.

2. Is it possible to recognize static postures using CSI of Wi-Fi signals?

   (a) If yes, how well could it be recognized?

   Yes, it is possible to recognize static postures using CSI values provided the environmental conditions remain unchanged. Given a stationary experimental setup, 5 different static postures could be recognized with an accuracy of about 80-90% in a usual office room and also in a controlled environment.

   (b) What could be the distinct features for static postures?

   For static postures instantaneous CSI values were used as the features. Among amplitude and phase, amplitude is informative for activity recognition. Amplitude data is also scaled with respect to AGC, mean and normal data (corresponding to no activity). All the scaled values are also informative and provide around 80-90% accuracy for the constant environmental conditions but do not help in making the system reliable.

3. Is it more feasible to have activity recognition as a sequence of static postures than dynamic activity recognition?

   No, static posture recognition are dependent on environmental conditions as well as the system fluctuations. Thus the absolute values do not show similar behavior when repeated over time. On the other hand, the signal behavior with respect to time for dynamic activities is more reliable.

5.2 Recommendations

As per our results static posture recognitions are not reliable even for ideal environmental condition in an anechoic chamber. We expect that the offsets in the subcarriers could be a possible reason for this. We know that off the shelf devices face such offsets during to manufacturing [26]. Phaser [33] explains how we can compensate for these effects in an existing WiFi hardware. A further study to find out the effects of frequency offsets on human activities could help to build up a reliable system.

Another approach to build a generalized activity recognition system is to break down usual day to day activities into simple dynamic activities. This method is similar to the shapes recognition as discussed in Section 4.3 of Chapter 4. For example, taking individual steps for left and right legs could be simple activities useful for recognizing walking, running and climbing stairs. Such an approach is expected to depend on time varying factors and independent of environmental factors. Thus this approach is more reliable approach for generalizing activity recognition using WiFi.

Bibliography

[1] "Lifestyle diseases: An economic burden on the health services," 2010. [Online]. Available: https://unchronicle.un.org/article/lifestyle-diseases-economic-burden-health-services

[2] "watchos 5 adds powerful activity and communications features to apple watch," ttps://www.apple.com/newsroom/2018/06/watchos-5-adds-powerful-activity-and-communications-features-to-apple-watch/, accessed: 2018-07-16.

[3] J. Chen, "Xbox kinect review: It's a brand new console," 2010. [Online]. Available: https://gizmodo.com/5680205/xbox-kinect-review-its-a-brand-new-console#

[4] F. Adib, C.-Y. Hsu, H. Mao, D. Katabi, and F. Durand, "Capturing the Human Figure Through a Wall," *Proceedings of ACM SIGGRAPH Asia 2015 Volume 34 Issue 6*, Nov. 2015.

[5] "Wisee uses wi-fi signals to recognise body gestures," https://www.bbc.com/news/technology-22780640, accessed: 2018-07-16.

[6] F. Foerster, M. Smeja, and J. Fahrenberg, "Detection of posture and motion by accelerometry: a validation study in ambulatory monitoring," *Computers in Human Behavior*, vol. 15, no. 5, pp. 571 – 583, 1999. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0747563299000370

[7] F. Adib, Z. Kabelac, D. Katabi, and R. C. Miller, "3D Tracking via Body Radio Reections," *Usenix NSDI'14, Seattle, WA*, Apr. 2014.

[8] F. Adib, Z. Kabelac, and D. Katabi, "Multi-Person Localization via RF Body Reflections," *Proceeding NSDI'15 Proceedings of the 12th USENIX Conference on Networked Systems Design and Implementation*, May 2015.

[9] M. H. Habaebi, M. Ali, M. Hassan, S. M. S., Z. A.A., K. A.A., W. W.S., and R. M., "Development of Physical Intrusion Detection System Using Wi-Fi / ZigBee RF

Signals," *2015 IEEE International Symposium on Robotics and Intelligent Sensors (IRIS 2015)*, 2015.

[10] S. Doong, "Counting Human Flow with Deep Neural Network ," *Proceedings of the 51st Hawaii International Conference on System Sciences*, 2018.

[11] C. Han, K. Wu, Y. Wang, and N. L.M., "WiFall: Device-free fall detection by wireless networks," *Proc.IEEE INFOCOM, Toronto, Canada*, 2014.

[12] W. Wang, X. Alex, and M. Shahzad, "Gait Recognition Using WiFi Signals," *Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, Sep. 2016.

[13] K. Ali, A. Liu, W. Wang, and M. Shahzad, "Keystroke Recognition Using WiFi Signals," *Proceedings of the 21st Annual International Conference on Mobile Computing and Networking*, Sep. 2015.

[14] S. Lee, Y. D. Park, Y. J. Suh, and S. Jeon, "Design and implementation of monitoring system for breathing and heart rate pattern using wifi signals," in *2018 15th IEEE Annual Consumer Communications Networking Conference (CCNC)*, Jan 2018.

[15] Q. Lin and Y. Yue, "Device-free Passive Human Detection using Wi-Fi Technology: Current State and Future Trend," *2015 IEEE 12th Intl Conf on Ubiquitous Intelligence and Computing*, Jul. 2016.

[16] M. Li, Y. Meng, J. Liu, H. Zhu, X. Liang, Y. Liu, and N. Ruan, "When CSI Meets Public WiFi: Inferring Your Mobile Phone Password via WiFi Signals," *Proceedings of the 2016 ACM SIGSAC Conference on Computer and Communications Security*, Oct. 2016.

[17] J. Ma, H. Wang, D. Zhang, Y. Wang, and Y. Wang, "A Survey on Wi-Fi based Contactless Activity Recognition," *2016 Intl IEEE Conferences on Ubiquitous Intelligence & Computing, Advanced and Trusted Computing, Scalable Computing and Communications, Cloud and Big Data Computing, Internet of People, and Smart World Congress*, 2016.

[18] M. Habaebi, M. Mahamat Ali, M. Hassan, M. Shoib, A. Zahrudin, A. Kamarulzaman, W. Wan Azhan, and M. Islam, "Development of physical intrusion detection system using wi-fi / zigbee rf signals," vol. 76, pp. 547–552, 12 2015.

[19] A. E. Kosba, A. Saeed, and M. Youssef, "RASID: A robust WLAN device-free passive motion detection system," *CoRR*, vol. abs/1105.6084, 2011. [Online]. Available: http://arxiv.org/abs/1105.6084

[20] C. Wang, S. Chen, Y. Yang, F. Hu, F. Liu, and J. Wu, "Literature Review on Wireless SensingWi-Fi Signal-Based Recognition of Human Activities," *Tsinghua Science and Technology*, Apr. 2018.

[21] "Evolution of 802.11 (physical layer)," https://www.okob.net/texts/mydocuments/80211physlayer/, accessed: 2018-04-26.

[22] L. Gong, W. Yang, D. Man, G. Dong, M. Yu, and J. Lv, "Wifi-based real-time calibration-free passive human motion detection," *Sensors*, vol. 15, 2015.

[23] K. Qian, C. Wu, Z. Yang, Y. Liu, F. He, and T. Xing, "Enabling contactless detection of moving humans with dynamic speeds using csi," *ACM Trans. Embed. Comput. Syst.*, Jan. 2018.

[24] A. Kalyanaraman, D. Hong, E. Soltanaghaei, and K. Whitehouse, "Forma track: Tracking people based on body shape," *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.*, Sep. 2017.

[25] Y. Wang, X. Jiang, R. Cao, and X. Wang, "Robust indoor human activity recognition using wireless signals," 2015.

[26] W. Wang, A. X. Liu, M. Shahzad, K. Ling, and S. Lu, "Understanding and modeling of wifi signal based human activity recognition," 2015.

[27] S. Yousefi, H. Narui, S. Dayal, S. Ermon, and S. Valaee, "A survey on behavior recognition using wifi channel state information," *IEEE Communications Magazine*, OCTOBER 2017.

[28] J. Zhang, B. Wei, W. Hu, and S. S. Kanhere, "Wifi-id: Human identification using wifi signal," in *2016 International Conference on Distributed Computing in Sensor Systems (DCOSS)*, May 2016.

[29] T. Xin, B. Guo, Z. Wang, M. Li, Z. Yu, and X. Zhou, "Freesense: Indoor human identification with wi-fi signals," in *2016 IEEE Global Communications Conference (GLOBECOM)*, Dec 2016.

[30] P. Wang, B. Guo, T. Xin, Z. Wang, and Z. Yu, "TinySense: Multi-User Respiration Detection using Wi-Fi CSI Signals," *2017 IEEE 19th International Conference on e-Health Networking, Applications and Services (Healthcom)*, 2017.

[31] "Linux 802.11n csi tool," https://dhalperi.github.io/linux-80211n-csitool/, accessed: 2018-04-25.

[32] "3m semi anechoic chamber," http://www.comtest.eu/products/anechoic-chambers/3m-semi-anechoic-chamber.html, accessed: 2018-08-13.

[33] J. Gjengset, J. Xiong, G. McPhillips, and K. Jamieson, “Phaser: Enabling phased array signal processing on commodity wifi access points,” in *Proceedings of the 20th Annual International Conference on Mobile Computing and Networking*, ser. MobiCom ’14, 2014, pp. 153–164. [Online]. Available: http://doi.acm.org/10.1145/2639108.2639139

Appendix A

Useful terminal commands for this project

This appendix covers some of the commonly used Linux commands useful for this project. The 3rd party project that we are using proposes to disable the wireless driver manager. So it is helpful to know the commands to control the wifi from the terminal. This is explained in section A.1. Further it may also be useful to know the commands to trace the CSI and set the required data and sampling rate of the network which is explained in section A.2.

A.1 Setting up WiFi

To connect to a wifi network, you may need the following commands: If the drivers are not loaded while the system boot-up, load the drivers by A.2 and A.2 and then follow the list of commands below:

1. Bring up the wireless LAN interface

   ```
   sudo ifconfig wlan0 up --to find the name of your interface use ifconfig
   ```

2. Connect to your wireless network

   ```
   sudo iw wlan0 connect "ESSID"
   ```

3. Check if the link is up

   ```
   iw wlan0 link
   ```

4. Request for IP address

```
sudo dhclient wlan0
```

5. If you want to check the Internet connection ping google.com

```
ping google.com
```

A.1.1 Some more supportive commands:

If you want to refresh the connection turn down the interface by

```
sudo ifconfig wlan0 down
```

and then follow all the steps from 1-5 again. If you want to reset only the IP address, send remove and reassign request to DH client

```
sudo dhclient -r wlan0 --remove
sudo dhclient -v wlan0 --reassign
```

To scan all the available networks

```
sudo iw wlan0 scan
sudo iwlist wlan0 scan
```

Find the address of gateway

```
netstat -rn
```

A.2 Setting up the parameters for drivers

Build the drivers, if made some changes in the driver code

```
make -C linux-80211n-csitool-supplementary/netlink
```

Unload the driver:

```
sudo modprobe -r iwlwifi mac80211
```

Reload the driver with CSI logging enabled

```
sudo modprobe iwlwifi connector_log=0x1
```

Get the APs MAC address:

```
sudo ls /sys/kernel/debug/ieee80211/phy0/netdev:wlan0/stations/
```

Check the existing data rates of the AP in the rate_scale_table by putting the MAC address in the command below. It can also be checked if the AP is currently in a High Throughput HT rate.

```
sudo cat /sys/kernel/debug/ieee80211/phy0/netdev:wlan0/stations/2c:fd:a1:67:31:6c/
```

Set the expected data rate

```
echo 0xc10D | sudo tee /sys/kernel/debug/ieee80211/phy0/netdev:wlan0/stations/2c:f
```

Start logging CSI to `csi.dat` file

```
sudo linux-80211n-csitool-supplementary/netlink/log_to_file csi.dat
```

To achieve a specific sampling rate ping the AP at interval specified after $-i$. Put the IP address of the AP at IP and mention the count of ping after $-c$. If the count is not specified, ping runs continuously until interrupted. IP address of the AP can be found by the next command.

```
sudo ping -i 0.05 (IP) -c (100)
```

IP address of the AP (usually 192.168.1.1):

```
arp -a
```

Appendix B

Rate_n_flags for setting WiFi attributes

This appendix explains the bit by bit values for setting the wireless parameters in a WiFi system using rate_n_flags.

Table B.1: Rate_n_flag bit fields

19	18	17	16	15
x	x	x	ant_C	ant_B
14	13	12	11	10
ant_A	short_guard_flag	dup_data	ch_40/20_flag	green_field_preamble
9	8	7	6	5
x	HT_flag	x	x	HT40_dup
4	3	2	1	0
stream_1	stream_0	rate_bit2	rate_bit1	rate_bit0

- bits [0:2] : used to select data rates. These may range values ranging from 0 to 7. For High Throughput (HT), the data rates could be set as follows:
    1. 0: 6 Mbps
    2. 1: 12 Mbps
    3. 2: 18 Mbps
    4. 3: 24 Mbps
    5. 4: 36 Mbps
    6. 5: 48 Mbps

7. 6: 54 Mbps
8. 7: 60 Mbps

- bits [4:3] : used to set the streaming type of the system
  1. 0: Single stream (SISO)
  2. 1: Dual stream (MIMO)
  3. 2: Triple stream (MIMO)
- bits [5]: high bit value indicates duplicate data for HT40.
- bits [8]: high bit value indicates HT type.
- bit [10]: high bit value enables green field preamble. Enabling this bit high means only HT communications are possible.
- bit[11]: high bit value indicates enabling 40 MHz channel.
- bit[13]:high bit value indicates short guard interval of 0.4 μsec and low bit value indicates normal guard interval of 0.8 μsec.
- bits[16:14]: each bit indicates transmit antennas ant_C, ant_B and ant_A for bit 16, 15 and 14 respectively. Setting the bits high indicates the antennas in use.

Appendix C

Details of Results for static posture recognition

This appendix gives the details of the results obtained for static postures for office room analysis and anechoic room analysis.

C.1 Office room data analysis

This section lists the accuracies for data taken in a office room with usual office furnitures present in it. Table C.1 lists the accuracies for experimental data taken in an office room for different features. The features include amplitude, phase, AGC profiled data and zero mean data.

Table C.1: Accuracies of individual days

Day/Data	Amplitude	Phase	Scaled Data-AGC	Zero-mean data
Day 1	84.20%	22.15%	93.61%	93.69%
Day 2	87.49%	20.83%	87.07%	87.38%
Day 3	91.02%	23.89%	98.28%	98.00%
Day 4	95.08%	20.21%	97.46%	96.74%
Day 5	96.80%	21.49%	98.52%	98.24%

Tables tables C.2 to C.4 list the accuracies for cross validated data for each day against the remaining days. Table C.2 lists the cross validation for amplitude data, Table C.3 for AGC profiled data and Table C.4 for zero mean data.

Table C.2: Accuracies of cross validation for amplitude data

Train(day)/Test(day)	1	2	3	4	5
1	-	19.57%	18.37%	22.61%	07.36%
2	34.76%	-	29.23%	06.55%	20.45%
3	32.13%	26.58%	-	01.40%	22.65%
4	01.55%	41.12%	06.21%	-	37.08%
5	17.03%	39.30%	23.76%	36.38%	-

Table C.3: Accuracies of cross validation for amplitude-AGC data

Train(day)/Test(day)	1	2	3	4	5
1	-	22.35%	19.17%	08.20%	34.40%
2	30.04%	-	02.88%	09.76%	19.94%
3	12.65%	16.70%	-	33.77%	24.41%
4	03.98%	26.76%	31.60%	-	19.96%
5	21.43%	10.55%	30.48%	19.70%	-

Table C.4: Accuracies of cross validation for zero mean data

Train(day)/Test(day)	1	2	3	4	5
1	-	12.07%	16.82%	02.96%	20.95%
2	30.50%	-	01.79%	24.42%	14.62%
3	07.40%	16.70%	-	34.90%	21.77%
4	11.99%	27.45%	30.41%	-	20.16%
5	35.91%	12.04%	31.39%	20.69%	-

C.2 Anechoic room data analysis

This section lists the accuracies for data taken in a anechoic chamber with controlled environment. Table C.1 lists the accuracies for experimental data taken in anechoic chamber for different features. The features include amplitude, AGC profiled data, zero mean data and normal profiled data.

Tables tables C.2 to C.4 list the accuracies for cross validated data for each day against the remaining days. Table C.2 lists the cross validation for amplitude data, Table C.3 for AGC profiled data and Table C.4 for zero mean data.

Table C.5: Accuracies of individual days for data in anechoic chamber

Day/Data	Amplitude	Scaled Data-AGC	Zero-mean data	Amplitude-null data
Day 1	88.63%	83.39%	80.10%	-
Day 2	89.32%	82.04%	93.61%	-
Day 3	98.43%	73.94%	98.27%	98.16%
Day 4	76.96%	78.39%	74.89%	71.76%
Day 5	92.72%	93.26%	92.59%	91.98%

Table C.6: Accuracies of cross validation for amplitude data

Train(day)/Test(day)	1	2	3	4	5
1	-	15.41%	15.17%	04.93%	19.21%
2	20.42%	-	18.86%	41.25%	20.27%
3	18.61%	22.25%	-	17.20%	28.44%
4	19.39%	17.20%	24.48%	-	18.35%
5	08.00%	21.08%	09.13%	11.02%	-

Table C.7: Accuracies of cross validation for zero mean data

Train(day)/Test(day)	1	2	3	4	5
1	-	20.79%	14.41%	04.59%	19.19%
2	17.06%	-	07.80%	34.98%	20.28%
3	18.65%	22.74%	-	10.51%	19.31%
4	20.67%	10.45%	28.70%	-	20.99%
5	06.81%	22.36%	06.91%	03.16%	-

Table C.8: Accuracies of cross validation for amplitude - AGC data

Train(day)/Test(day)	1	2	3	4	5
1	-	24.06%	16.55%	30.42%	19.21%
2	16.74%	-	10.97%	31.59%	20.09%
3	18.65%	22.25%	-	10.45%	19.28%
4	19.37%	19.45%	27.52%	-	14.79%
5	10.52%	21.01%	21.30%	20.79%	-

Table C.9: Accuracies of cross validation for normal profiled data

Train(day)/Test(day)	1	2	3
1	-	05.71%	17.20%
2	14.99%	-	20.80%
3	10.21%	16.24%	-