CONTACTLESS HUMAN ACTIVITY RECOGNITION

By

Brandon Lamont Harrington

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ABSTRACT

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The objective of this thesis is to design passive measurement and classification systems to recognize various human activities. Human Activity Recognition (HAR) can enhance a diverse range of human-centric applications in health care, smart homes, and security. Traditional solutions are based on wearable sensors and vision-based technologies; however, these solutions suffer from considerable limitations. The need for users to wear sensors for activity recognition is inconvenient and impractical for long periods of time. Contactless HAR systems have increased the abilities, practicality, and convenience of sensor based HAR systems. It allows for unobtrusive measurement and classification of sedentary behaviors in the workplace such as time spent sitting at desk, to intense physical activities such as at home exercises. This thesis provides contributions to contactless HAR methods and techniques using different sensing modalities. While activity recognition can be achieved with low cost ultrasound sensors, we show the beneficial impact of adopting radio frequency as a technological means of recognizing human activity. Specifically, WiFi signal analysis enables both macro and micro level activity classification. The ubiquity of WiFi infrastructures in home, university, work, and even outdoor environments makes WiFi the most convenient technology to produce valuable contributions in human activity recognition.

The primary contributions of this work are: 1) Development of prototype hardware system, Echolocation Activity Detector (EAD), that achieves contactless activity recognition in office setting. 2) A low-cost system that employs WiFi monitoring of packets to provide a student engagement measure, and 3) Design of a non-invasive system that recognizes exercise activity and provides fine-grained repetition counting information of each exercise set using WiFi channel state information. Each of the contributions passively detects and classifies human activity in a contactless fashion without the need of wearable sensors.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

1. Introduction

In recent years, Human Activity Recognition (HAR) has become an essential paradigm in countless applications that enhance the health, safety and overall well-being of all humans. Human activities are essentially a set of particular actions and movements in a given environment. A human activity recognition system aims to recognize these actions to provide activity specific information or gain contextual information about the surrounding environment. This information can be used to analyze and understand human behavioral patterns. Traditionally, low-cost wearable sensors (e.g. accelerometers) fueled the development of sensor-based HAR systems [1-2] that utilize valuable sensor data to classify human activities. For example, wearable sensors are extremely useful in healthcare applications where the real-time sensor information alerts proper personnel of fallen elderly patients in distress. However, the need for users to wear sensors for activity recognition is inconvenient and impractical for long periods of time. This unavoidable limitation has dramatically increased the need for contactless human activity recognition systems [3-5]. Contactless HAR systems have increased the abilities, practicality, and convenience of sensor based HAR systems. It allows for unobtrusive measurement and classification of sedentary behaviors in the workplace such as time spent sitting at desk, to intense physical activities such as at home exercises. With unique system configurations and novel features extracted from collected sensor data, this work provides contributions to contactless HAR methods and techniques.

1.1. Focus of Research

This work presents an alternative to wearable sensors by classifying human activity with a fixed sensor placement. A fixed sensor placement approach allows for uninterrupted data collection since the collection is not dependent on subjects wearing devices to initiate a data collection session. Ultrasound sensors are low-cost sensors used for many ranging and level detection applications, making it a great sensing modality for sensors with a fixed placement. This work utilizes ultrasound sensors for detecting numerous office setting activities. A benefit of using a sound source for activity recognition is the lack of interference from the ubiquitous RF devices. Despite RF rich office environments, ultrasound was used to confidently classify human activities in office setting. On the other hand, the sensing range with ultrasound is limited due to the fixed directionality of the transmitter. If a subject is not in the sensing range of the sensor then no data is collected. Limited sensing range can be a limiting factor in regard to human activity recognition. While activity recognition can be achieved with low cost ultrasound sensors, we show the beneficial impact of adopting radio frequency as a technological means of recognizing human activity. Specifically, WiFi signal analysis enables both macro and micro level activity classification. The ubiquity of WiFi infrastructures in home, university, work, and even outdoor environments makes WiFi the most convenient technology to passively detect and classify human activity without the need of wearable sensors.

1.2. Contactless Sensing Technologies

1.2.1. Ultrasound

Ultrasound frequency range begins at 20kHz, just above human audible sounds, and can extend past 10 MHz. An ultrasound sensor uses one or multiple transducers to send and receive ultrasonic pulses. The data received from the sensor generally corresponds to an object's proximity to the sensor. High-frequency sound waves reflect from objects to produce distinct echo patterns. When transmitting, the transducer converts the electrical energy into sound after which the sound wave is transmitted. Upon receiving the echo, the sound waves are converted into electrical energy which can be measured and analyzed. Often, ultrasonic sensors are placed into arrays to capture more information than a single sensor. Typical applications that utilize ultrasonic sensors include healthcare, home automation, energy efficient buildings etc. These low-power, low-cost sensors make ultrasound an ideal technology for recognizing various human activities.

1.2.2. Radio Frequency (RF)

The frequencies of radio waves range from 3 kHz to 300 GHz. RF signals can cover a large distance and can penetrate opaque objects like wall and human body. Many RF communication systems that have been deployed in industry and in our daily life use different frequency ranges to communicate. The variety of RF technologies utilized for RF sensing applications such as Bluetooth [6], Zigbee [7], Radio Frequency

Identification Device (RFID) [8], and WiFi [9], stem from the various communication ranges established within the radio frequency range.

Bluetooth. Bluetooth is used to transfer data over short distances. It is defined in IEEE 802.15.1 as a form of Wireless personal area networks (WPAN). The latest version of Bluetooth, i.e., Bluetooth Low Energy (BLE), can provide an improved data rate of 24Mbps and coverage range of 70-100 meters with higher energy efficiency, as compared to older versions [6]. Due to Bluetooth's low cost and complexity, it is present in most modern wireless devices, however, the range of applications is typically limited to localization.

ZigBee. Zigbee is built upon the IEEE 802.15.4 standard that is concerned with the physical and MAC layers for low cost, low data rate and energy efficient personal area networks [7]. Zigbee is heavily used in Wireless Sensor Networks (WSN). The Application Layer is responsible for distributed communication between nodes. The Network Layer in Zigbee is responsible for multi hop routing and network organization. ZigBee is used often for localization in sensor networks; however, a drawback is that it is not readily available on majority of the wireless devices.

Radio Frequency Identification Device (RFID). RFID is a wireless data-capturing technique that utilizes RF waves to store and retrieve data between reader and tags that are generally attached to objects. RFID signals are affected by the surroundings so changes in the environment can be observed by monitoring by features of RFID signals. RFID signal features include RSSI and phase which can be obtained from a RFID reader [8]. There are two types of RFID systems. An active RFID system depends on the internal power supply to reflect a response to the reader. Although longer ranges can be achieved, active RFID systems usually have a higher cost and larger form factor. Passive RFID tags draw much attention because of their smaller size and lower cost, and no need for power sources. A drawback of RFID is the need for additional hardware.

WiFi. WiFi is perhaps the most popular technique used for RF sensing. Recent advances in wireless technology have found that the WiFi signals are sensitive enough to capture environmental dynamics thus can be used for the sensing purpose [9]. WiFi based sensing makes it possible to deploy sensing tasks on existing infrastructures, since WiFi access points are ubiquitous in typical indoor settings. Additionally, WiFi is non-invasive sensing. The presence of humans and their related body movements will have considerable impact on surrounding wireless signals, thus human body movements involved in daily activities can be passively captured and classified. Sensing tasks can be accomplished without user awareness which provides no discomfort. For the above reasons, we utilize WiFi, instead of other RF modalities, to achieve contactless human activity recognition.

1.3. Sensing Techniques

1.3.1. First-Reflection Echolocation

Ultrasonic sensors emit ultrasonic waves to measure distance by keeping track of the time required to receive an echo of the transmitted pulse. Very little processing and computational overhead is required to calculate the distance data. The distance of the object that reflected the transmitted sound wave can be calculated with the following formula:

$$D = T \times C \times \frac{1}{2} \tag{1}$$

where D is the distance, T is the time between the transmission and reception, and C is the speed of sound constant. The value is multiplied by 1/2 since T accounts for the total round-trip time of the signal.

1.3.2. Received Signal Strength Indicator (RSSI)

In RF wireless systems, RSSI is the measured power of a received radio signal. It is implemented in IEEE 802.11 standards. For most widely used wireless techniques ranging from UWB, ZigBee, and WiFi to cellular networks, RSSI is easily accessible. RSSI indicates the path loss of a received wireless signal with respect to the distance of the transmitter [10]. The loss of signal strength that occur between transmitter and receiver is known as propagation path loss. Path loss is a major factor when analyzing wireless communication systems. Various propagation models have been developed to predict the loss of signal strength between transmitter and receiver. A commonly used propagation model that predicts the path loss with respect to distance is the logarithmic distance path loss model [11]. It is noted that the average received signal power decreases with the log of distance. In this work we obtain RSSI values of received radio packets where the RSSI is expressed using the log-distance path loss model. According to the path loss model, the path loss between any transmitter and receiver can be expressed as:

$$PL_{(d)} = PL_{(d_0)} + 10nlog_{10}\frac{d}{d_0} \tag{2}$$

where d is the distance, d_0 is the reference point at 1m, and n is the path loss exponent [11]. The higher the RSSI values, the stronger the signal. The main drawback of RSSI measurement is that it's not stable in complex indoor environments. RSSI not only varies over distance but also suffers from shadow fading and multipath fading. RSSI also fluctuates over time even at a static link because of the multipath effect. However, in typical indoor environments, wireless signals often propagate via multiple paths called multipath propagation. With sever multipath propagation, RSSI may no longer decrease monotonically with propagation distance, thus limiting ranging accuracy. Multipath propagation can also lead to unpredictable RSSI fluctuations. Studies showed that RSS can fluctuate up to 5dB in one minute even for a static link [11]. Since RSSI is a single-valued, it fails to convey knowledge about multipath propagation, making it less robust and less reliable.

1.3.3. Channel State Information (CSI)

In wireless communication, CSI is a representation of the channel properties of a communication link. As signals propagate through multiple paths, each of the paths leads to different amplitude attenuation, phase shift, and time delay. orthogonal frequency division multiplexing (OFDM) technology is a bandwidth-efficient multi-subcarrier modulation scheme that combats multipath propagation, enabling signals to be reliably received [12]. In OFDM, signals are transmitted over orthogonal frequencies, which are called subcarriers. Based on OFDM, CSI describes the channel properties of a communication link and is able to distinguish multipath propagation at the subcarriers level. Channel measurement at the subcarrier is available on modern devices that adopt obey IEEE 802.11n/ac standard which permits multiple transmit and receive antennas for multiple-input multiple-output communication in wireless communication. Therefore, CSI reveals fine-grained characteristics of wireless signals combining effect of time delay, amplitude attenuation, and phase shift of multiple paths on each communication subcarrier. The WiFi signal can be modeled as Channel Impulse Response (CIR) h(τ) in frequency domain:

$$h(\tau) = \sum_{l=1}^{L} \alpha_l e^{j\phi_l} \delta(\tau - \tau_l) \tag{3}$$

where α_l and φ_l represent the amplitude and phase of the l-th multi-path component respectively [12]. τ_l is the time delay, L indicates the total number of multi-path and δ(τ) denotes the Dirac delta function. The time domain channel response h(t) can be derived by taking the Inverse Fourier Transform (IFFT) of the Channel Frequency Response (CFR). Every preamble of OFDM symbols that is transmitted can generate a channel matrix estimation from WiFi devices. This channel matrix, otherwise known as, CSI is represented by:

$$H_i = \|H_i\| e^{j\angle H_i} \tag{4}$$

where both amplitude and phase information can be extracted [12]. The multipath effect, which is normally detrimental for data communication, can have a beneficial effect on WiFi. The quantitative analysis of signal propagation behavior within a WiFi-covered area can identify and measure different types of disturbances. CSI represents the coefficient of a wireless channel and the CSI of every sub-carrier is a complex number. The CSI of a packet transmitted with M transmitting antennas, N receiving antennas, 20MHz channel bandwidth, is a complex matrix of size M×N×56. If the bandwidth is 40MHz, then the size of CSI matrix becomes M×N×114. Typical systems have multiple input multiple output (MIMO) antenna configuration. Figure 1 gives an overview of an M×N MIMO system with M transmitting antennae and N receiving antenna. Environmental changes and human body movements affect the CSI values of different links independently, but the effect on different subcarriers of each link may be correlated. Authors in [13] developed the CSI tool that can extract the CSI from Wi-Fi implementing the IEEE 802.11n standard using a Network Interface Card (NIC) with Atheros chipset. 802.11a/g/n receivers implements an OFDM system with 56 subcarriers for each receive antenna, therefore, fine grained changes in the wireless channel can be observed.

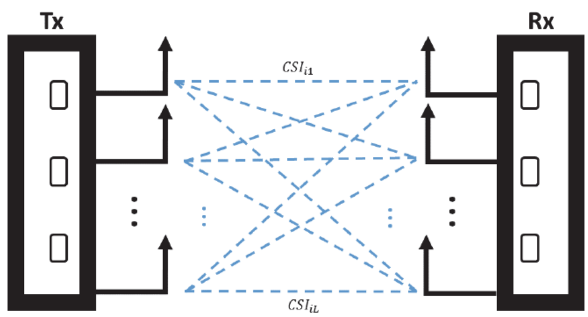


Figure 1-1: Schematic representation of signal propagation between Tx-Rx antennas

1.4. Research Objectives

In this work, several research objectives were met to produce valuable contributions in human activity recognition.

1.4.1 Human activity analysis using ultrasound

An ultrasound echolocation-based approach for human activity recognition in indoor settings was developed to differentiate between typical workplace activities such as sitting, standing, and walking. The key novelty of the system is to perform activity analysis using time-series distance data estimated through first-reflection echolocation. With the use of supervised machine learning mechanisms, extracted features were used to classify the unique signatures of different activities, a novel contactless method to passively monitor human activity in office setting was developed. The complete system is a practical human monitoring device that can replace the traditionally used wearable devices.

1.4.2 Student engagement measurement using Wi-Fi RSSI

Collective Wi-Fi RSSI measurements from classroom generated web traffic was leveraged to develop a passive monitoring system with the objective of providing a contactless method to obtain classroom engagement levels. The system monitors wireless network traffic on both 2.4GHz and 5GHz ISM bands in a university classroom setting to enable capture of spatiotemporal contextual knowledge of students' mobile device usage. By capturing spatiotemporal usage of mobile devices during lectures, student engagement levels can be estimated in real-time using the resulting time-series data of generated web traffic intensity. The system's ability to capture extended use of ubiquitous mobile devices during classroom lectures is unobtrusive and free from human involvement, consensus, or bias. Additionally, the design of the low-cost system yields a feasible approach of automatic measurement of student engagement at very high frequency (e.g. lecture-to-lecture). Therefore, the developed system provides as an instructional tool to easily and frequently measure and analyze the effects of various classroom dynamics in order to enhance instructor performance, increase student engagement, thus improving overall quality of education in university classroom settings.

1.4.3 Human activity analysis using Wi-Fi CSI

The channel state information of multiple Wi-Fi communication links between two mobile devices was analyzed to recognize human exercises, namely push-ups, and autonomously provide detailed repetition data to track volume and frequency of physical activity across time without the use of wearable sensors. The effect of periodic movements that human bodies create on nearby wireless signals can be observed and characterized to obtain sufficient contextual knowledge regarding specific physical exercises. Since Wi-Fi CSI is obtained from signals modulated using ODFM, subcarrier level analysis was conducted to identify fine-grained movements. Specifically, we show that the correlation of subcarrier amplitude variations between subsequent received packets facilitates the separation of exercise data from non-exercise data. Various pre-processing techniques were used to prepare the obtained CSI data for correlation feature extraction, yielding high machine learning classification results. Additionally, through spectrogram analysis, the number of repetitions of an exercise can be determined and after multiple activity intervals the stored exercise data provides a historical physical activity level database for the user. More importantly, we aim to extend the current literature convention of restricted device placement and orientation when developing a system to detect or differentiate between various human exercises. By exploiting antenna diversity as well as subcarrier level analysis, we demonstrate that exercise data can be accurately classified and analyzed with an unconventional device placement and orientation.

1.5. Organization of Thesis

In Chapter 2, a thorough literature review of human activity recognition work is presented. In addition, comparisons were made to highlight and differentiate the contributions of the proposed work from the contributions in the reviewed literature. Contactless activity recognition via the developed prototype hardware system, Echolocation Activity Detector (EAD), that is capable of measuring object distance using ultrasound echolocation with first reflection is presented in Chapter 3. The low-cost system, Student Engagement Measurements and INstructor Assessments in Realtime (SEMINAR), is discussed in Chapter 4 where several drawbacks of current student engagement measurement methods are addressed by the proposed system. Chapter 5 emphasizes the motivation to design Wi-Fi based human activity recognition systems as Wi-Fi CSI data analysis enables classification capabilities that cannot be obtained using ultrasound. The developed monitoring system can successfully classify can pushup exercise data and count the number of repetitions. Chapter 6 provides a detailed summary and conclusion of the presented work.

2. Related Work

We review related activity recognition work of each proposed scheme, respectively. Our proposed office activity classification system via echolocation is first compared with existing ultrasound-based activity recognition approaches. Next, we distinguish our proposed Wi-Fi monitoring based approach for measuring student engagement in university classroom from existing Wi-Fi monitoring works in university settings. Finally, we thoroughly review existing CSI-based exercise activity recognition approaches and outline limitations of current systems which motivate the proposed exercise recognition system.

(i) Ultrasound Based Human Activity Recognition Approaches

Ultrasonic echolocation is used in [14] for mapping a person's surroundings for navigation applications. In this approach, the human subject that is navigating is required to wear the developed echolocation device, so that audible cues translated from reflected ultrasound signal can be acted upon for effective navigation. While this work utilizes ultrasound to gain context regarding the human's environment, human activity is not explicitly classified in this work. Additionally, the system is a wearable device, and therefore suffers from the same limitations as sensor-based activity recognition systems. Echolocation is used for automatic fall detection in [15] and breathing monitoring in [16]. Both works use full-reflected signal analysis to detect movements of their respective activities, movements of a human fall and chest movements caused by breathing. A drawback of these works is the hardware computational complexities of the signal analysis. Our approach which only uses first-reflection analysis saves on computational resources as opposed to full-reflected signal analysis. The approaches reported in [17,18,19] target contactless activity analysis using ultrasound echolocation and the applications in those papers are similar to our target application. However, all of those approaches also rely on full-reflected signal analysis. By converting the first ultrasound reflection to a signal that provides the distance between the echolocation device and the nearest obstructing object, a low-complexity post-processing system for activity classification is presented.

(ii) Wi-Fi Monitoring Based Activity Analysis in Classroom Settings

Researchers in [20] developed EDUM, an education measurement system that measures class punctuality (if students were on time, late, or attended a class at all) and lecture attractiveness. EDUM uses device-specific personal data including MAC address of mobile phone, student identification number, and course schedule of specific students. Class attendance is determined by recording the RSSI of an individual's MAC address seen by the access points inside or near the classroom. In addition, EDUM requires installation of two mobile apps on phones of students. Using the installed apps, lecture attractiveness is measured by recording the ratio of time a user's mobile phone screen state reported ON with respect to the length of the class lecture. This work is limited in that it requires students to volunteer in participating via installing and using a third-party App. Students may not always be open to that, especially if they know that the App will be used for tracking their device usage.

The work in [21] addressed the problem of restricting network access inside specific university classrooms. A two-part system containing an Ethernet bridge with a web-based control panel and a WiFi monitoring station was used. The Ethernet bridge was installed at the edge of the campus' Intranet, with the goal of using a web-based control panel to modify traffic flow rules that will ultimately limit which internal network traffic is able to leave the campus network. A WiFi monitor is placed inside a classroom to monitor probe packets that will determine which MAC addresses are inside the classroom. Over Ethernet, the monitor sends a list of current MAC addresses to a database containing a list of classrooms and MAC addresses that are inside of those classrooms. Given that the instructor wants to restrict network access, packets containing these MAC addresses can then be filtered out and discarded by the system's traffic controller. This work does not attempt to gain behavioral knowledge of students rather it aims to restrict Internet access from devices in a room by using a WiFi monitor to develop a list of nearby MAC addresses whose Internet access should be restricted. This can cause trouble for nearby devices that broadcast a probe packet that is seen by the monitor and is mistaken to be inside the classroom.

The paper in [22] investigated wireless traffic patterns in a university library and auditorium via WiFi monitoring. Several monitors are deployed throughout both locations with the primary purpose of capturing individual device MAC addresses obtained from periodic probe requests. As a result, researchers are able to determine occupancy levels in each of the buildings for different times of the day as well as provide information regarding the average stay duration of the devices. Similarly, [23] performs end user profiling in university environment. One dataset was collected from monitoring inside a classroom and another from the research lab of the authors. Regarding user profiling, authors proposed a set of features to be extracted from the capture time of probe request frames to cluster users in groups (e.g. lab members or visitors) based on their dwell time and presence. Using the dataset collected in a classroom, authors show that probe requests can be used to distinguish between smartphone and laptop.

A tool aimed at supporting instructors with identification and localization of students in the classroom is presented in [24]. This system requires knowledge of MAC addresses for all students enrolled in the class. Using Wi-Fi monitoring, the authors implement a localization technique and map the MAC address of a located device to a student currently enrolled in the course. Information regarding which students are present is then provided to the instructor.

Our proposed system differs from the above works in the following aspects. First, and most important, the above works do not attempt to gauge student engagement. [20] attempts to measure lecture attractiveness by providing a ratio of active screen time to the duration of the lecture, however, this is ineffective when students view lecture slides from their devices. Secondly, unlike many of the above approaches, SEMINAR requires no student participation such as mobile App installation, which makes the SEMINAR approach more practical and feasible than many of the approaches discussed above. In addition to not being dependent on students' voluntary participations, the SEMINAR approach does not depend on continuous monitoring from human observers, thus this approach is not vulnerable to students being able to intentionally adjust their classroom behavior in order to thwart any measurement efforts. Third, many of the approaches discussed above require tracking device MAC address level information that is mapped to student Ids, thus raising privacy concerns. The SEMINAR approach avoids such information collection and mapping to student IDs. Fourth, unlike some of the approaches above, the measurement approach in SEMINAR is agnostic to the underlying encryption used by the mobile devices. This is achieved by concentrating mainly on aggregated traffic volume, and not device-specific traffic for which management frames need to be probed. Encryption can block the visibility of the management frames such as the probe frames, thus limiting the effectiveness of gathering device-specific information. In SEMINAR, traffic volume can be measured even when the lower layer management information is blocked using various encryption methods. Finally, the work presented in this chapter specifically aims at gathering knowledge of device usage rather than attempting to detect the presence of or restrict the network access of a device in a specific location, as targeted by some of the above approaches. These differences clearly distinguish SEMINAR from current relevant literature that employ Wi-Fi monitoring in university settings to gain contextual information.

(iii) Contactless Exercise Activity Recognition

Contactless physical fitness and exercise monitoring has been extensively studied literature. In [25], accelerometer sensors are embedded into glove to recognize and track various free-weight exercises conducted by human subject. While high activity recognition accuracy is obtained, the requirement of wearing dedicated sensors, especially for exercise activity recognition, may be unsuitable. A passive RFID based free-weight exercise recognition system in [26] attaches passive RFID tags to the training devices, i.e., dumbbell in this work, and leverages the backscattered signal for activity recognition. While RFID tags are not wearable sensors, this is a sensor-based method that requires many sensors for widescale implementation thus, practical implementation is limited. [27] aims to help the user to achieve effective workout and prevent injury by dynamically depicting the short-term and long-term picture of a user’s workout based on various sensors in common mobile devices. The above works achieve the goal of contactless exercise monitoring; however, wearable sensor-based implementations have a significant drawback. Despite its small size and light weight, sensor-based systems require the user to wear the device or keep it within close proximity for detection. The need to wear a sensing device to monitor physical exercises is eliminated with Wi-Fi based activity recognition, such as the proposed system.

Earlier Wi-Fi based contactless activity recognition systems utilized RSSI as the sensing measurement. [28] proposed the concept of device-free passive localization using RSSI and present a passive radio map construction to enabled device location tracking. Behind the wall localizing and tracking and localizing of a target using a statistical model of RSSI variance was proposed in [29]. [30] and [31] employed RSSI for gesture recognition and intruder detection, respectively. Since RSSI is a very simple metric and does not require any special hardware changes using RSSI for human activity recognition is very easy, but RSSI suffers from severe multipath fading, distortions and instability in complex environments. Regarding the granularity of information from the obtained data, RSSI is a coarse-grained information and it does not leverage the subcarriers of an OFDM channel like CSI. Fine-grained information can be obtained from advanced approaches that employ CSI to passively detect human activity since collected data of CSI is richer than that of RSSI.

Activity recognition via CSI as the sensing measurement enables recognition of more specific activities both fine and coarse grained such as smoking [32], breathing [33], and various gestures [34]. Keystrokes from a continuously typed sentence can be identified with high accuracy in [35]. The number of people in a crowd can be determined using CSI values by treating the human subjects reflecting the Wi-Fi signals as virtual antennas in [36]. [37-39] all proposed a passive human detection scheme which exploits multi-path variations for detecting human presence in an indoor environment using CSI.

While there is extensive work done in activity recognition using CSI as a whole, the proposed work in this thesis aims detect physical exercise using CSI, avoiding any wearable device. Current works that also aim to achieve contactless detection or monitoring of physical exercises are [40-42]. [40] proposed a CSI-based green system for exercise activity recognition and quality evaluation. A novel method is proposed to use the complete CSI-waveform shape as a feature to successfully detect the starts and ends of each action. Although this work relies on the training data and selected features, the systems suffers when the deployment environment is not static. The Fresnel Zone diffraction model is leveraged in [41] to understand the principle behind Wi-Fi sensing effects and can detect various exercise activities. While this can accurately distinguish between different exercises the placement and orientation of the Tx and Rx devices are constrained so the potential for practical system deployment in real world is decreased. [42] developed a system capable of differentiating users that execute the exercise. The system uses a Deep Nueral Network based model to perform fine-grained workout interpretation and to provide smart workout assessment. This work also implements a system whose placement and orientation of the Tx and Rx devices are constrained, which motivates the proposed work.

The human activity recognition system that we propose sets us apart from current literature that uses CSI for exercise activity monitoring because we aim to lessen the placement constraints of the receiving device. Contrary to literature's standard convention on Tx-Rx placement and orientation. Currently, existing approaches place the CSI transmitting and receiving devices 3-5 meters apart where the respective height and orientation of each CSI device is equal. To increase system flexibility and practicality our work decouples the height, orientation, and physical placement of the receiving device from the CSI transmitting device by taking advantage of the fined-grained contextual information embedded in CSI data of subsequent packets at the receiver. This allows the transmitter (e.g. Access Point) to be fixed while the receiver's position and placement is at the users' digression. Presented in this work is our system's ability to accurately differentiate exercise data from non-exercise data with a Tx-Rx placement consisting of different device height and orientation. Additionally, with advanced signal de-noising methods and novel feature extraction, we prove that exercise statistics such as number of repetitions can still be determined with a non-standard device placement.

3. Contactless Indoor Activity Analysis using First-reflection Echolocation

This chapter presents an ultrasound echolocation-based approach for human activity recognition in indoor settings. The key novelty of the proposed approach is to perform activity analysis using distance estimated through first-reflection echolocation where the distance to the nearest obstructing object is computed using the first reflected ultrasound signal. All subsequent reflected signal components from other distant objects are ignored. This leads to an extremely simple signal (i.e., time-series distance data) analysis approach with very low computational complexity. Especially so, when compared with the existing approaches in literature in which full reflected signal analysis, often with Doppler Shift computation, is performed for activity classification. It is demonstrated that for the goal of isolating workplace sedentary behavior, the proposed approach can differentiate between sitting, standing, and walking (i.e., in-office pacing) with more than 80% accuracy. This was validated with different classifiers applied on data collected from multiple subjects in multiple sessions. Recorded video was used as the ground-truth for training the classifiers.

3.1. Introduction

In recent years, human activity monitoring and analysis have gathered significant attention [43] from medical researchers as well as health-conscious consumers. Majority of activity monitoring devices use multi-axes accelerometers and gyroscopes [44] to detect body movements in order to detect human activities with various granularities. Human activity is being considered as one of the primary actionable indices within the evolving framework of *quantified self* [44]. Research indicates [45] that presenting one's activity data in a meaningful manner can improve one's overall lifestyle both in terms of dietary and physical activity habits, thus alleviating heart disease, diabetes, depression, and other health risks. Recent proliferation of wearable activity monitoring devices from Apple, Samsung, Sony, Fitbit, Garmin, and other vendors indicate the exploding consumer interest for activity monitoring.

While the wearable devices offer ubiquity and continuity of monitoring, a major limitation is that a consumer does have to actually wear them for continuous monitoring in both indoor and outdoor settings.

Many recent studies suggest [46] that in addition to the disadvantages of losing and having to remember to regularly wear, the interest in such devices tend to wane within a fairly short period. This is more so for healthy gadget-enthusiasts, for whom the interests in such devices typically do not last for more than three to six months [47]. Although it is gradually becoming less of an issue, the lack of cosmetic appeal of such devices in certain situations can deter people from using them.

One way to eliminate the need for wearing devices is to monitor activity by analyzing video footage from strategically placed cameras. However, video would work only in indoor settings, thus operating with much less ubiquity compared to the wearable solutions. A bigger issue with video is its intrusive nature leading to privacy concerns. Additionally, any real-time feedback or intervention process based on video-monitored activities requires complex image processing which is not the case for wearable device-based solutions. Availability of proper lighting conditions can also pose a challenge for such image processing tasks.

In this chapter, we propose a privacy-preserving activity monitoring using ultrasound SONAR, which is used by many mammals including bats, dolphins, and whales. The key idea is to emit ultrasound pulses towards an individual and to analyze the reflected sound signal for estimating the current activity of the individual. This, however, requires an ultrasound transceiver unit to be placed by the subject individual, thus limiting the ubiquity of the approach mainly to applications in indoor settings. Its utility is also limited when multiple subjects are simultaneously visible by the SONAR transceiver.

In spite of such constraints, this technique can be leveraged in many niche applications including indoor monitoring: (a) of an individual in her/his office/cubicle where a significant number of the waking hours are spent, (b) in living room, (c) an elderly person staying home alone, and (d) sleep analysis. In many of these situations, having a continuously running SONAR unit in one or multiple places within a home/office can offer a more practical and reliable solution compared to the ones that mandate the monitored subject to wear a monitoring device without fail.

Specific contributions of the chapter are as follows. First, a prototype hardware system that is capable of measuring object distance using ultrasound echolocation with first reflection was designed. Using only the first reflection as opposed to full reflection analysis, as done in many approaches in the literature, offers an activity analysis approach with ultra-low computational complexity. Second, a set of detailed experiments, involving work-place activities, for multiple subjects were conducted for collecting echolocation data and ground-truth video data. Finally, multiple features were designed for using the echolocation data in order to perform contact-less activity classification.

3.2. Experimental System

All the experiments and validation results presented in this work are targeted towards monitoring an individual in the workplace. Fig 3-1 shows the prototype Echolocation-based Activity Detector (EAD), which is placed on a desk by the office occupant. The EAD unit contains a microprocessor (ATmega328P on Arduino Uno R2 platform [48]) that collects data from an array of ultrasonic echolocation sensors (HRLV-MaxSonar EZ1 Ultrasonic Sensor [49]). The sensor data is then post-processed for classification of the activities.

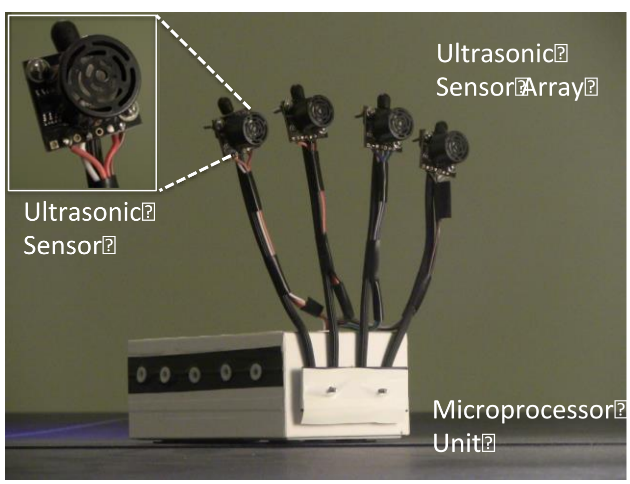


Figure 3-1: Prototype EAD Device

The sensor HRLV-MaxSonar uses 42 KHz ultrasound pulses and computes object distances with millimeter resolution based on the first major reflected signal. As reported in its spec sheet, reliable distance measurement can be done for objects placed from 11 inches up to 170 inches. It should be noted that these simple sensors with small form-factor (approximately 0.5in x 0.5in x 0.5in) do not full-reflected signal analysis for detailed terrain recovery. Instead, they only measure the timing of the signal transmission and that of the first reflected signal in order to compute the distance of the nearest obstructing object. All subsequent analysis for activity classification is performed on time-series distance data. Note that although the prototype contains an array of four sensors, the results in this work are based on the data obtained from a single sensor.

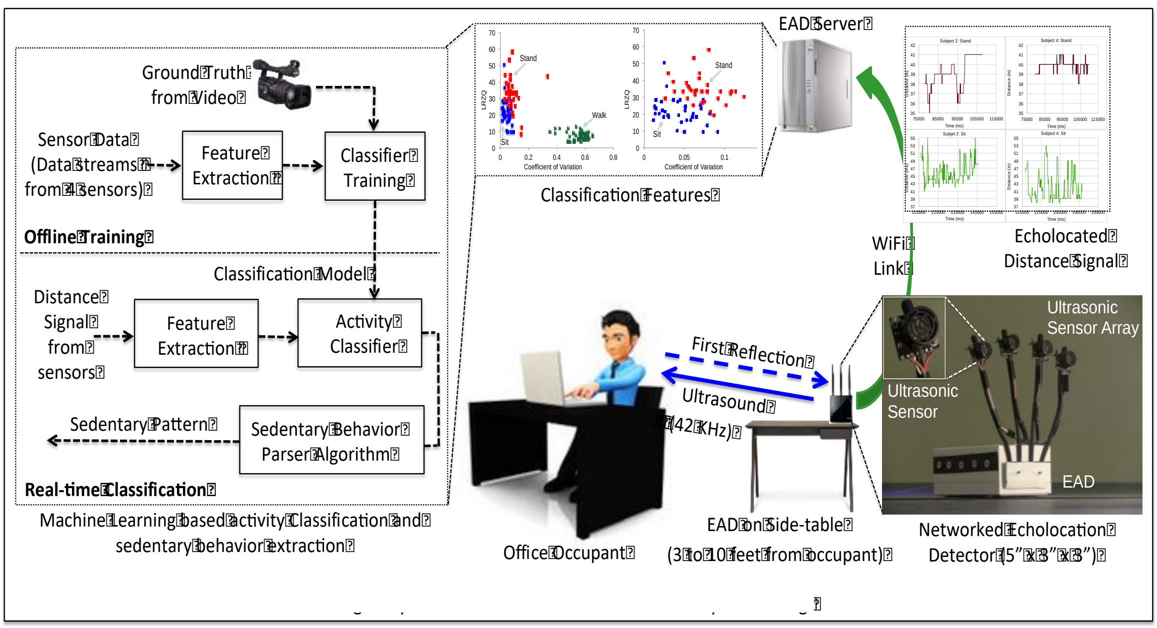


Figure 3-2: System architecture for contactless activity monitoring

We target the problem of classifying three typical work-place activities, namely, sit, stand, and walk (i.e., in-office pacing). Studies have shown [50] that these activities can often reliably indicate sedentary behavior, thus able to predict various health outcomes. Data was collected from six subject individuals. For each person, each of the three target activities (i.e., sit, walk, and stand) was performed for six different sessions, each lasting for around 30 seconds. During a session, the EAD unit was placed at an approximate distance of 3 to 10 feet from the occupant's chair, and the EAD sensor facing the middle part of the occupant's torso. Time-series distance data between the EAD and the subject was collected during the entire session. The hypothesis is that the measured distance and its variation can provide unique signatures for each of the targeted activities. Video recording was done for capturing the actual activity states, which are then used as the ground truth during machine-assisted activity classification. Note that the EAD unit and the video recorder were kept in data collection mode even when the subjects walked out of the office. This allowed sensor-based office occupancy detection.

Figure 3-2 depicts the overall system components to show how the EAD is placed by an office occupant, such that the sensors generally face the occupant. It collects first-reflection ultrasound signal to be able to compute distance of human-objects located from approximately 11 inches up to 170 inches with millimeter level resolution. Time series distance data that result from the subject's movements are sent to an EAD server through WiFi link.

Activity classification software: The left part of Figure 3-2 shows the classification software in the EAD server. It has an offline training component in which a classifier is trained for activity classification using sensor data and the ground truth obtained from time-stamped video footage. The trained classification model is then used during real-time classification. Using live data stream from the EAD, activities are classified as sit, stand, or walk, and fed into a sedentary behavior parser algorithm, which extracts sedentary behavior statistics.

3.3. Activity Classification

The key classification steps in this section are: (1) feature design and extraction from time-series distance data, (2) classifier training, and (3) performance validation.

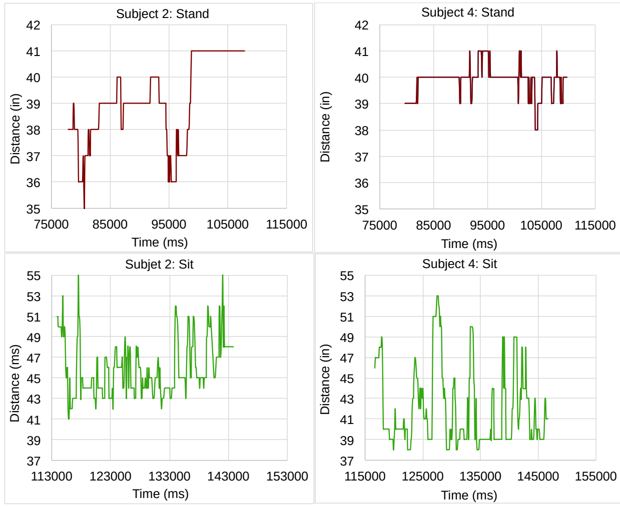


Figure 3-3: Raw time-series distance data from the prototype EAD

Sample time-series distance data for two most common workplace activities, namely, sit and stand, are shown in Figure 3-3 for one female and one male subject. As can be seen, between sit and stand, the former consistently produces higher distance variations. The reason is that higher lower-body stability during the sitting posture allows one to sway the upper-torso more often than in standing posture when the overall stability is less. Since the sensor was targeted towards the subjects' middle torso and the sensing-lobe width (i.e., at the subject-EAD distance of 36 inches to 60 inches) is approximately 50 inches, the sensor was able to capture the sway of the upper torso in terms of the distance variations as shown in Figure 3-3. It was consistently observed that walking produces much higher distance variations when compared to sit and stand. This is because the subject's distance from the sensor varies significantly when she/he walks away or towards the EAD device.

3.3.1. Distance Variation as the Classification Feature

Based on the above observation of distance variability for different activities, we used Coefficient of Variation (COV) of the measured distance as the classification feature. COVs of the time series distance data are computed for each 30 sec. session, and the corresponding actual activity (i.e., the ground truth) for the corresponding window is marked from the video recording.

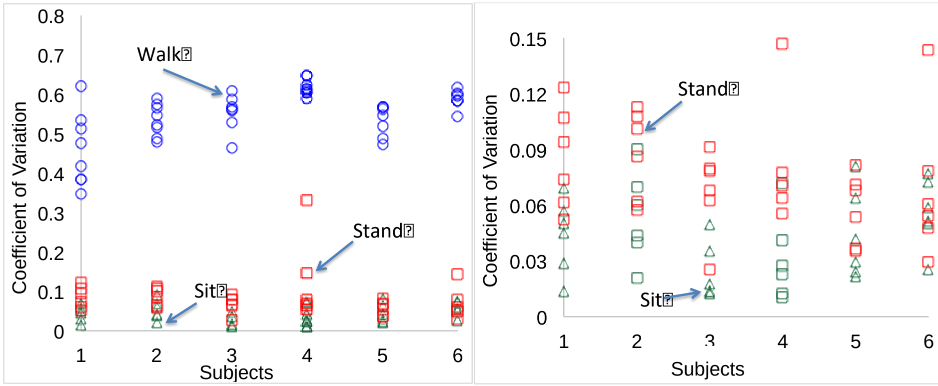


Figure 3-4: Class distinctions using distance-COV

The left panel in Figure 3-4 depicts the COVs for all three activities. Each point in the graph represents the COV of the distance values measured over a 30 sec period. The COV is computed over 300 samples collected at the rate of 10Hz for 30 seconds. Observe that the high distance variability for walking clearly differentiates the points for walking from those for sitting and standing, thus indicating the suitability of distance-COV as a classification feature for walking. For instance, a threshold COV of around 0.3 is sufficient to separate out the walking events with almost no loss of accuracy. Between sitting and standing, however, the COV demonstrates significant overlapping, which is more apparent in the zoomed-in version of the graph, as shown in the right panel in Figure 3-3. Such overlapping would lead to loss of classification accuracy while separating standing and sitting. Figure 3-5 shows how, after the walking events are separated out, those classification accuracies individually change for different thresholds chosen for the distance-COV.

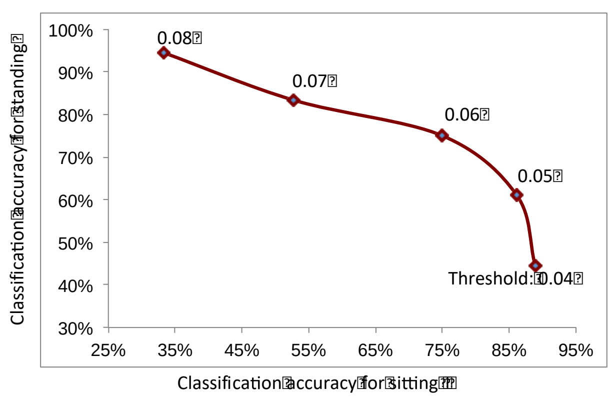


Figure 3-5: Sitting and standing classification accuracies

From these results, it can be concluded that using distance-COV as the single classification feature may not always be sufficient for simultaneous accurate classification of the sitting and standing activities. This leads to the two-feature classification solution as presented below.

3.3.2. Linear Regression Zero-crossing Quotient as the Second Feature

The sample distance data in Figure 3-3 demonstrates that even though its variability during standing and sitting are not significantly different, sitting produces a higher frequency signal. This general pattern was observed in all the data collected for all subjects. This observation led to the following addition of a frequency domain feature for improved classification.

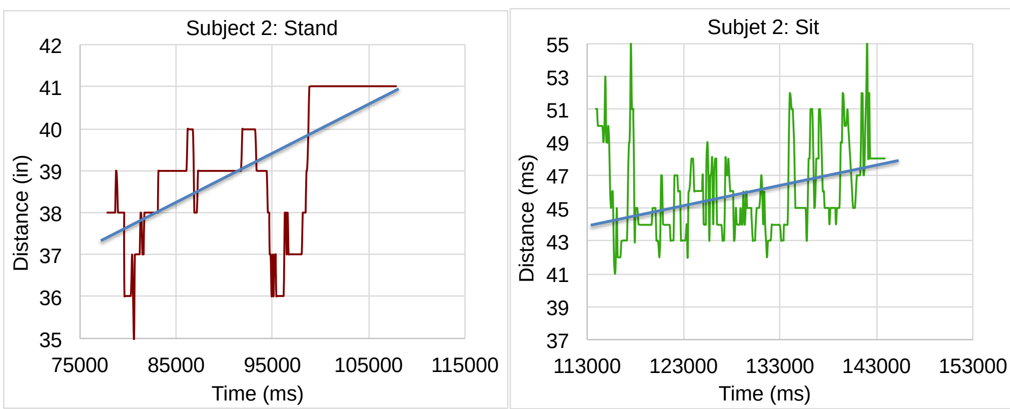


Figure 3-6: Using LRZQ for capturing frequency in distance signals

Linear Regression Zero-crossing Quotient (LRZQ) is used for capturing the frequency of variability as follows. First, as shown in Figure 3-6, linear regression of the distance values is computed. Then the count of how many times a signal touched or crossed this line was recorded. This count, termed as the LRZQ, indicates the general frequency content of the signal in question. For example, it is evident from Figure 3-6 that the LRZQ for sitting is significantly larger than that for standing. This was generally observed for all collected data for all subjects. As done for the COV feature, the LRZQ values are computed for each 30 sec period of the collected data. Note that LRZQ, instead of Fast Fourier Transform (FFT) based spectral density computation, was used for maintaining computational simplicity and the subsequent ease of run-time classification abilities within an embedded setting.

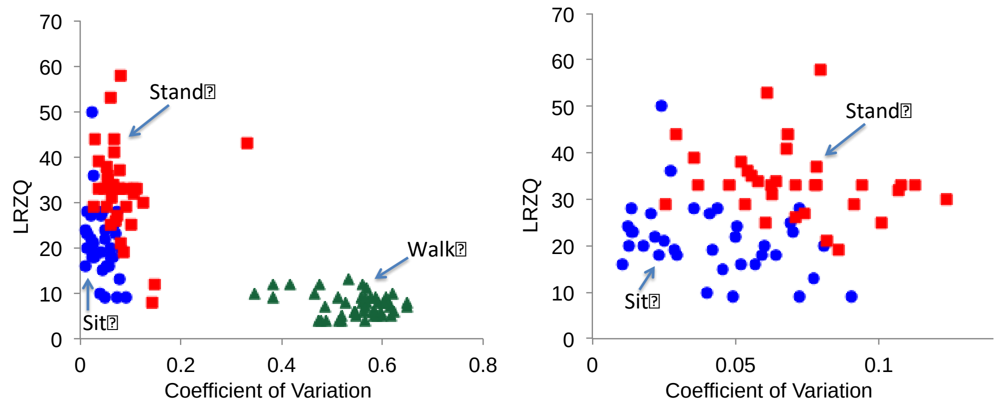


Figure 3-7: Two-feature scatterplots for all three activities

The left panel in Figure 3-7 shows the scatterplot of COV and LRZQ for all collected data for all three activities for all subjects. Each point on the graph indicates the COV and LRZQ computed over one session (i.e., 30 sec) worth of distance data. Observe that for walking, while the COV is higher than the other two activities, its LRZQ is quite small, because the periodicity in movement is of the order of walking strides, which is high compared to those for sitting and standing. This causes a very distinct point cluster for walking. Consequently, similar to the one-feature classification case, walking can be easily classified against the other two activities.

The right panel in Figure 3-7 shows the zoomed-in scatter plots only for sitting and standing. It should be noted that in this two-feature scenario the clusters for these two activities are much more separable compared to the COV-only scenario in Figure 3-4. With COV and LRZQ as the features. Three different classifiers, namely, Logistics, Naïve Bayes, and Sequential Minimal Optimizer (SMO) were tried with 90-10 validation method. In this method, 90% of randomly chosen data points are used for supervised training of a classifier and the remaining 10% of the data are used for validation purposes.

Table. 3-1: Performance of two-feature classification

	Logistics			**Naïve Bayes**			**SMO**	
	Precision	**Recall**		**Precision**	**Recall**		**Precision**	**Recall**
Stand	88%	83%		80%	89%		81%	99%
Sit	84%	86%		88%	78%		93%	78%
Walk	98%	100%		100%	100%		100%	100%
Overall	91%	91%		90%	90%		92%	92%

Table 3-1 summarizes the classification performance in terms of *precision* and *recall*. Precision (also termed as positive predictive value) for a class (e.g., sitting) represents the percentage of all classified activities that are actually sitting. Recall (also termed as sensitivity) represents the percentage of actual sitting activities that are classified as sitting. Table 3-1 shows excellent classification performance (i.e., more than 80% for all classes) with all three classifiers.

3.4. Conclusions and Future Work

We proposed and implemented a novel contact-less human activity monitoring method that uses ultrasound-based echolocation utilizing only the first reflection, indicating the distance to the nearest obstructing object. The key idea is to use a SONAR-based Echolocation based Activity Detector (EAD) that sends ultrasound signal towards an individual's torso and analyzes the reflected signal to determine the distance of the closest point on the torso. The time-series distance data contains signatures of different activities, which are detected by classifying those signatures using supervised machine learning mechanisms. Using a prototype EAD, developed in our laboratory, we demonstrate the effectiveness of the approach for a specific application of work-place activity analysis. Three typical work-place activities, namely, sit, stand, and walk (i.e., in-office pacing) are detected using the echolocation signal. It was shown that using a two-feature classification approach, it is possible to identify such activities with more than 80% accuracy over many subjects and activity sessions.

Future work on this topic includes: a) experimenting with run-time classification with the goal of providing real-time feedback, b) exploring Fast Fourier Transform (FFT) spectral components as classification features, c) using a sensor array for improved spatial resolution of the distance data, d) scaling up the system for more activities applicable for a larger set of applications, and e) characterization of the system under ultrasonic ambient noise, often produced by motors in home/office appliances.

In the next chapter, we transition from ultrasound to WiFi as the sensing measurement to attain contactless human activity classification.

4. A Student Engagement Measurement System via Passive WiFi Monitoring

A contactless method to obtain collective classroom engagement levels is presented in this chapter. The ubiquity of mobile devices and wireless infrastructures in university classrooms have aided student learning experience in recent years. Among other things, using such technology, the students are able to follow along lecture slides and search through key concepts from the Internet in real time in order to better comprehend the instruction material. While aiding learning experiences, these devices can also be used for non-academic Internet browsing, which is a major source of distraction, and can negatively impact the overall quality of education. This work attempts to measure spatiotemporal usage of mobile devices during lectures by passively monitoring WiFi traffic generated inside classrooms. Such measured data can be used to determine student engagement in real-time. Using temporal patterns of classroom generated WiFi traffic, the proposed system can generate automatic measurements of student engagement in real time, and for longer durations in various time scales. The work proposed in this chapter demonstrates the feasibility of a practical WiFi traffic monitoring system that implements a contactless approach to monitor student activity with regard to use of mobile device within the classroom. Ultimately, the system can be used as an instructional tool to measure and improve student engagement in university classroom settings.

4.1. Introduction

Wireless infrastructures in universities have become ubiquitous over the past decade. The advancements and ubiquity of such wireless infrastructures have significantly fueled the increase in number of mobile devices. A 2017 study [51] shows 97% of college students own smartphones and 95% of college students own laptops. Many students use such mobile devices to take notes and/or follow along lecture slides. While these mobile devices can aid classroom learning, they can also contribute to student distractions and negatively impact the quality of education. The objective of this work is to develop a system for estimating such distractions in an unobtrusive manner.

Student engagement in higher education is heavily researched in the discipline of educational psychology [52] and it is proven that higher levels of student engagement has a strong link to greater academic success and achievements [53]. Work pertaining to student engagement can be grouped into the following categories: defining and understanding student engagement [54], understanding how student engagement affects quality of education [55], and methods of measuring student engagement [56]. We attempt to measure student engagement using the proposed system, **S**tudent **E**ngagement **M**easurements and **IN**structor **A**ssessments in **R**ealtime (SEMINAR).

SEMINAR is a passive network traffic monitoring system that provides spatiotemporal knowledge of mobile device usage inside a classroom, which can provide a reliable and real-time measurement of student engagement during a classroom lecture.

Definition of Student Engagement. Student engagement has three interrelated aspects: behavioral, cognitive, and emotional. This work focuses on the behavioral aspect which encompasses positive student behaviors including effort, participation, attendance, and compliance with other classroom norms [57]. Based on our hypothesis of a correlation between in-class mobile device usage and student distractions, for this chapter, we define student engagement as the absence of distraction induced by extended non-academic use of mobile devices.

The key idea of the proposed framework is to passively monitor in-class WiFi network traffic so that mobile device usage inside a classroom can be estimated. In literature, applications of WiFi monitoring include localization [58], crowd sensing [59], and facility management [60]. SEMINAR makes use of data frames captured, contrary to the vast majority of WiFi monitoring works that only make use of management frames. Data collected by the system is collective, and so, privacy related issues tied to device-specific data collection are avoided. The complete construct and implementation of our low-cost, classroom specific, and passive monitoring system are discussed in this work.

Obtaining knowledge regarding student engagement is extremely beneficial as it provides instructors and university administrators the ability to monitor and improve courses with the ultimate goal of improving the quality of education. A drawback of current state of the art observational student engagement measurements is that observers generally observe a sample of students in a class rather than the whole class. In addition, this method requires a consensus of student behavior among all observers. The most significant drawback of observational methods, as well as other methods (e.g. student/teacher self-assessments, questionnaires, etc.) is that engagement measurements are concluded the moment observers discontinue their observations or questionnaires are no longer distributed. The aforementioned drawbacks raise a question that motivates our current work. *After obtaining results of classroom engagement via conventional measurement methods, how can instructors be sure that changes in lecture dynamics (e.g. teaching style, presentation of material, etc.) to improve student engagement continue to make positive impacts*? In other words, it is difficult to continually gauge the retention of corrective instructional measures using the traditional methods.

This is difficult due to the high operational costs such as constant human presence for student observations, and it is often unreasonable to believe that current measurement methods can be consistently conducted to allow instructors to assess their students' engagement on a day-to-day, month-to-month, or even semester-to-semester basis. However, engagement measurements at high frequency may provide a better understanding as to how methods and practice of teaching are linked to student engagement.

The proposed system, SEMINAR, addresses many of the challenges and drawbacks of current student engagement monitoring measures. Specifically, it can provide unobtrusive temporal and spatial engagement measurements in real-time to instructors. In this chapter we present and showcase the ability of the system to measure WiFi traffic volume that can be used to provide measurements of student engagement inside a classroom. We also demonstrate and highlight the feasibility of automatic measurement of engagement at very high frequency (e.g. lecture-to-lecture) without any human involvement.

Specific contributions of the chapter are as follows. First, it presents the framework of a system that passively monitors wireless network traffic on both 2.4GHz and 5GHz ISM bands in a university classroom setting to enable capture of spatiotemporal contextual knowledge of students' mobile device usage. Second, it demonstrates how extended use of ubiquitous mobile devices can provide a measure of student engagement that is free from human involvement, consensus, or bias. Finally, the chapter showcases the feasibility of the proposed system to be effectively used in a slew of upper level applications that will be developed using the developed measurement framework.

The rest of the chapter is organized as follows. Section 4.2 presents the overall system architecture and Section 4.3 outlines the system set-up procedure. Extensive analyses of collected data is presented in Section 4.4 and a discussion of our current and future work is presented in Section 4.5. The chapter concludes with Section 4.6 which provides the conclusions of this work.

4.2. System Overview

In this section we discuss our current dataset and how data is collected. We also provide details regarding our system design and set-up.

4.2.1. Dataset Description

The data collected in this work was collected by attending multiple lectures of a second-year engineering course throughout a 14-week semester. It should be noted that in this particular course, there were no online notes or class material provided. The instructor generated all class notes in real time; as a result, there was no immediate need to access the Internet during the lectures. Collected data is used to demonstrate the abilities and feasibility of the presented SEMINAR system. Also, to be noted that the main goal is to capture a collective view of the classroom traffic, and therefore, no a priori student device-specific information is collected.

4.2.2. Wireless Infrastructure

The WiFi infrastructure in university buildings on our campus consist of multiple IEEE 802.11 access points (AP) manufactured by Aruba or Cisco that are distributed throughout the corridors of each building. A wireless distribution system (WDS) is implemented, effectively broadcasting 2 SSIDs primarily used by occupants to gain Internet access anywhere on campus, *MSUnet* and *MSUnet Guest*. Each AP may broadcast multiple SSIDs covering both 2.4GHz and 5GHz ISM bands which utilizes many of the available WiFi channels. Since there are no APs located inside classrooms, the current wireless infrastructure makes it difficult to monitor the amount of traffic in one specific room. Furthermore, gaining access to view data from specific APs that are closest to the target classroom would result in unusable information since data to and from each AP can be from any of the surrounding rooms.

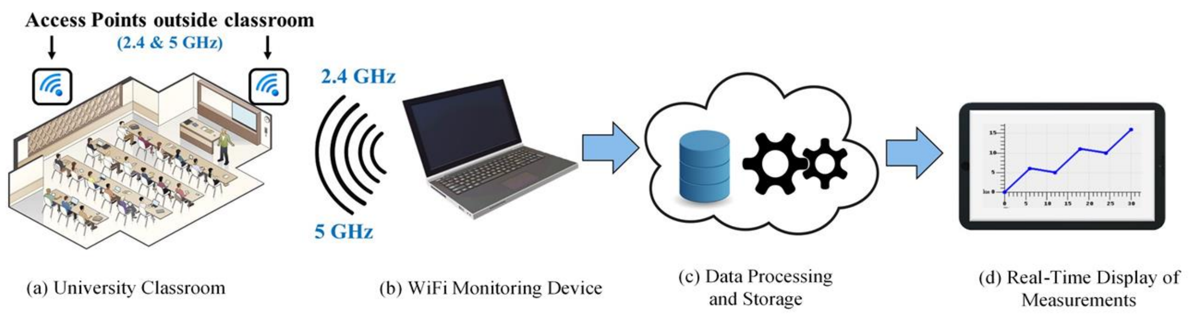


Figure 4-1: Different Components of the SEMINAR System Architecture

4.2.3. Data Collection, Filtering, and Processing

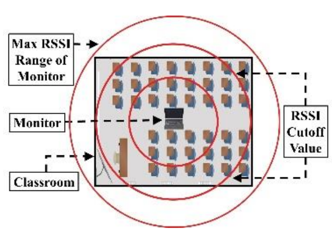
As depicted in Figure 4-1a, data is collected in a university classroom. Our monitoring device, shown in Figure 4-1b, is a Toshiba laptop with a Linux operating system (OS) installed. It should be noted that any laptop with a standard network interface card installed is able to enter monitor mode; Linux OS makes it easier to control the network interfaces. The monitor is equipped with 2 WiFi interfaces in monitor mode to allow sufficient data capture in both 2.4 and 5 GHz frequency ranges. Channels used in 2.4 GHz band are 1,6, and 11, so one WiFi interface monitors these channels at a rate of 3 channels per second. After initial analyses of wireless infrastructure, it is observed that there are 4 channels in the 5 GHz band that are primarily used by devices in the classroom. As a result, the second interface is used to monitor channels 36, 48, 60, and 161 at a rate of 4 channels per second.

The collected data is wirelessly sent to a storage database where filtering and processing occurs. We measure the volume of uplink data frames generated by devices inside a classroom, so we filter out management and control packets. In addition, we filter out downlink data frames since these frames are transmitted by APs located outside the classroom. Finally, to extract only data generated by devices inside a classroom, we filter out frames with RSSI value outside of our determined RSSI cutoff value as discussed in the next subsection.

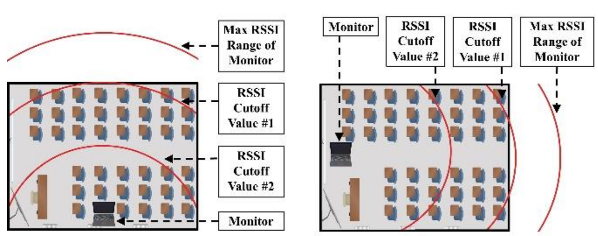
After filtering out all unneeded data, the remaining data is processed and wirelessly sent to a viewing platform (i.e. tablets, iPads, or laptops) owned by instructor. This enables real-time display of current measurements. Currently displayed is raw traffic intensity measurements; however, the next step is to correlate these measurements to a level of engagement and display engagement levels as well.

4.2.4. WiFi Monitor Placement and RSSI Cutoff Values

For our system to provide reliable spatiotemporal Wifi traffic analyses, monitor placement is a crucial step in the data collection. A WiFi monitor is placed in the center of a classroom as in Figure 4-2a to capture collective WiFi usage in the classroom over time. For more granular information, it can be determined how much WiFi traffic each section of a classroom (front, back, left, or right) generates by also placing monitors in locations shown in Figure 4-2b. These placement locations are further referred to as edge placements. Depending on the size of a classroom, the effective monitoring range of a monitor may extend past the walls of a room; in this case it is imperative to have a RSSI cutoff value determined. This is visualized in Figure 4- 2. For brevity, we refer to the RSSI Cutoff Value as RCV. When a monitor is placed in the center of a room as in Fig 4-2a, only one RCV is needed. Monitors at edge placements (Fig 4-2b) require two RCVs, one for the far end of the room and another that is used to approximate the midway point of the room. Determining an RCV to approximate the middle of the room effectively allows measurements to be divided between front and back of classroom. Similarly, the midpoint RCV allows the room to be divided into left and right sections.



(a) Front Monitor Placement



(b) Edge Monitor Placements

Figure 4-2: Monitor Placements for Data Collection

4.3. SEMINAR Set-Up Procedure

Before SEMINAR can be effectively used, an initial set-up procedure must be executed to determine the needed RCVs. Since the topology and size of a classroom are two features that effect the RCV, this set-up procedure must be executed anytime the system is deployed in a new classroom. To highlight the feasibility of using the proposed system in university settings, it is worth noting that the set-up procedure can be completed in as little as 15 minutes by one user. All that is needed are two mobile devices (further referred to as set-up devices) actively generating continuous WiFi traffic (e.g. Youtube video) in addition to one WiFi monitor. These set-up devices should be connected to the campus's wireless network and the MAC address of each device should be accessible. By providing the MAC address for each device, the system monitors the surrounding environment only capturing packets from the specified MAC addresses, ultimately reducing the processing needed to determine the cutoff values. The idea is to use RSSI readings from set-up devices to determine RCVs (shown in Figure 4-2) which will enable monitored traffic to be classified as inside or outside the room. RCV #2 for edge placements (Figure 4-2b) allows traffic classified as inside the classroom to be further labeled as: *front* or *back* and *left* or *right*. A python set-up script that automatically determines the RCVs was created to aid the easy deployment. The script contains concise instructions and little human involvement is needed. A sample output of set-up script is shown in Figure 4-3.

```
Initiating SEMINAR system set-up...

Enter 2 MAC addresses for RCV determination:
xx:xx:xx:xx:xx:x1 xx:xx:xx:xx:xx:x2

(Placement 1 of 3) Place monitor in center of classroom...
Place devices in diagonally opposite corners...
Please move away from monitor while monitoring is in process...
Press enter to begin...

Traffic Monitoring is in progress, please wait...
Monitoring is concluded. One moment please...
RSSI Cutoff Value for center placement is: -62 dbm.
Press enter to begin next placement...

(Placement 2 of 3) Place monitor in front of classroom...
```

Figure 4-3: Sample Output of SEMINAR Set-Up Script

Identifying the RSSI Cutoff Value. The goal of this procedure is to obtain an RCV that will maximize the capture of traffic generated inside the classroom while minimizing the capture of traffic that is not. Two key factors contribute to the accomplishment this goal. For this explanation we focus on the identification of the center monitor RCV, depicted in Figure 4-4a. The first key factor is the strategic corner placement of set-up devices when determining the RCV. The diagonally opposite corners correspond to the furthest distance from the center monitor, and since attenuation increases with distance, the average signal strength of packets from a set-up device is representative of the minimum received signal strength that should be observed from packets generated inside the classroom. This factor maximizes the capture of traffic generated inside the class. Captured traffic from outside of the room is minimized due to the natural characteristics of wireless links where attenuation of signal strength increases as it propagates through matter (e.g. concrete wall). The distance between the monitor and the outside of the classroom in addition to the concrete walls of the classroom effectively decreases signal strength of packets not generated inside the class. As a result, majority of RSSI readings of outside devices are not within the acceptable range of RSSI values dictated by the RCV. The distribution of RSSI readings acquired from each set-up device is examined to determine a RCV such that at least 50% of packets generated by each individual device can be seen by the monitor is chosen. Similarly, set-up devices are placed as shown in Figure 4-4b for determining edge monitor RCVs; and as discussed in the previous section, two RSSI cutoff values are determined for these monitor placements.

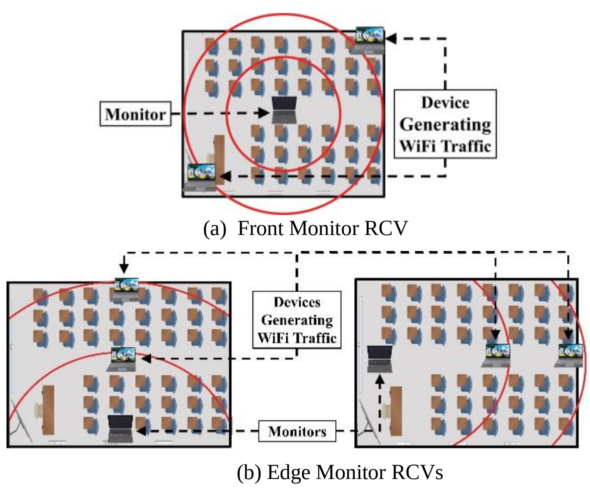


Figure 4-4: Monitor Placements for Set-Up Procedure

4.4. Dataset Analysis

In this section we analyze data from the SEMINAR dataset, illustrating natural trends of WiFi traffic generated by students' mobile devices during class lectures. In addition, the ability of the proposed system to capture both short-term (e.g. minute to minute) and long-term (e.g. month to month) temporal patterns in classroom WiFi usage is presented in this section. As discussed in Section 3a, the current dataset consists of multiple monitoring sessions of a single 50-minute course with one instructor. All class notes were generated during the lecture and no online class material was provided. As a result, students are expected to pay close attention to lecture in order to copy the generated notes as there was no expressed need to access the Internet. Therefore, our analysis highlights the ability for SEMINAR to provide significant insight into mobile device usage during lectures, ultimately leading to development of a collective classroom engagement measure based on mobile device usage.

4.4.1. Validity of Collected Dataset

Figure 4-5 illustrates the validity of the collected dataset, proving that the data collected is representative of the WiFi traffic dynamics inside of the classroom. During this particular data collection, we begin collecting data at 3:25pm, 45 minutes before the start of the lecture that will be monitored. At the start of the collection there were already 15 students in the classroom waiting for the lecture to begin. From that point on we recorded the number of students that entered the room per minute. This can be seen by the red line in Figure 4-5. We overlay the 4-minute moving average of the total amount of data frames that remains after the filtering process described in Section 3C. Since the lecture had not yet began, many students were active on their mobile devices. A strong correlation is observed between the number of students and WiFi activity in the classroom; the volume of traffic generated per minute increases as the occupancy level increases. At 4:10pm the lecture begins, as well as a dramatic decline in the amount of traffic generated in the classroom. At 4:45pm the students in the classroom are explicitly asked to browse the Internet on their mobile devices. This browsing session can also be observed in Figure 4-5. The class is dismissed at 5:00pm and students began to exit. Due to large groups of students departing all at once, recording the number of students that departed per minute was infeasible. We instead record the time at which the departure of students concludes. At that time, the total amount of data frames captured falls to zero. Ultimately, Figure 4-5 illustrates the responsiveness of the proposed system as well as the validity of the data collected.

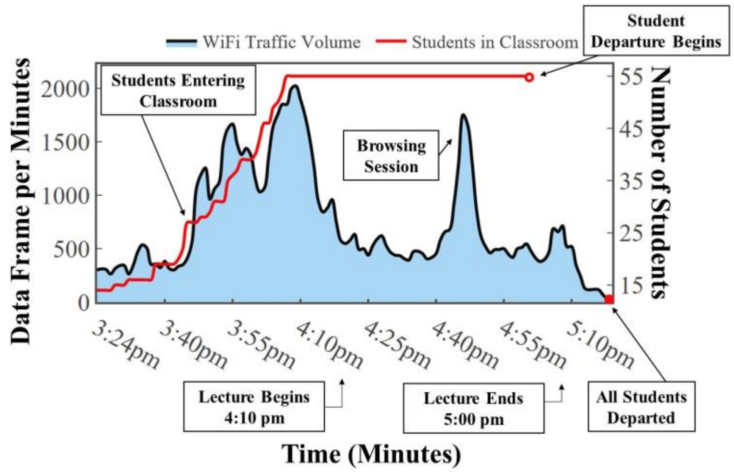
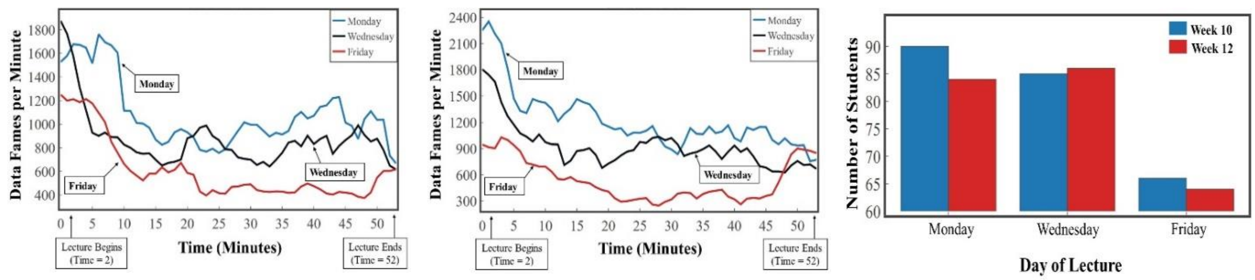


Figure 4-5: Responsiveness of Monitoring System

4.4.2. Weekly Patterns of Mobile Device Usage

The monitored course was held three times a week (i.e. Monday, Wednesday, Friday), and data collection occurred multiple weeks throughout the semester. Monitoring sessions began two minutes prior to the start of class and concluded two minutes after the end of class. In Figure 4-6 traffic patterns can be observed for two different weeks in the semester, Week 10 (Figure 4-6a) and Week 12 (Figure 4- 6a). As shown in both Fig 4-6a and 4-6b, there is a time interval at the beginning of the lecture where the intensity of WiFi traffic is high and decreases throughout the first few minutes of the class. We refer to this as the Lecture Settle-in Time (LST). The LST varies from day to day, for example, Monday's traffic intensity in Week 10 (Figure 4-6a) remained near 1600 packets per minute until about minute 9 where a sharp decline is observed. Conversely, on Wednesday of the same week the decline occurred much earlier than it did on Monday; effectively demonstrating that after the lecture begins, mobile device usage declines at various rates. Identifying factors that affect LST is part of our future work motivation, linking our traffic measurements to levels of engagement and analyzing various class dynamics that may induce unengaged behavior such as browsing on mobile devices during class time. As a result, we could potentially conclude that larger Lecture Settle-in Times corresponds to students' disregard for the instructor beginning the lecture, instructor unpreparedness or tardiness, or simply a lack of interest or engagement for the current lecture topic.



(a) Week 10 Traffic Patterns (b) Week 12 Traffic Patterns (c) Number of Students Present During Lecture

Figure 4-6: Mobile Device Usage for Different Weeks

In Figure 4-6c, the number of students who attended lecture each of the days shown in Figure 4-6a and 4-6b is plotted. On Fridays, less students attend the lecture. This trend is observed throughout the entire semester. Consequently, the total generated data on Fridays is significantly less than it other days of the week as shown in both Week 10 and Week 12 in the figure below. In addition, the intensity of traffic at the start of data collection (two minutes before the lecture begins) on Fridays is significantly lower than Mondays and Wednesdays.

4.4.3. Best-Case Scenario for Maximum Student Engagement

Figure 4-7 displays four sets of data collected: Two normal Friday lectures and two exam day lectures that were given on a Friday. Several key conclusions can be derived from the results displayed in the figure: 1) The volume of traffic generated during normal Friday lectures is substantially more than the traffic volume generated during Friday exams. It should be noted that nearly all students are present on the day of exams while nearly a fourth of students are typically not present on a regular Friday (Figure 4-6c). Even with more students present during exam day, the substantial decrease in traffic volume on those days is expected because all mobile devices are put away during the duration of the exam. Since mobile device usage is prohibited during exams and extremely low traffic volume on those days are observed (Figure 4-

7) as opposed to normal Friday lectures where there is no restriction on mobile device usage, the validity and responsiveness of the proposed system is also demonstrated here.

2) Exam day data provides the best-case scenario for engagement measurement. As mentioned above, mobile device usage during exams is prohibited thus Figure 4-7 exam days can represent a day in which all students are fully engaged and there is no Internet browsing. Notice that the traffic intensity does not reach zero, this is expected as many devices have background applications running. In addition, the duration of the LST on exam days is shorter when compared to normal Fridays or even other days of the week from Figure 4-6.

3) There is significant variation in traffic patterns when comparing the two normal Fridays lectures. More specifically, during the time interval t=20 minutes to t=35 minutes, the traffic intensity of Normal Friday #1 is noticeably greater than that of Normal Friday #2. The reason for the variation is not the focus of this work, however, it supports our hypothesis of a correlation between mobile device usage and classroom engagement. Ultimately, it motivates our future work of using the volume of WiFi traffic generated within a classroom as an estimator of student engagement.

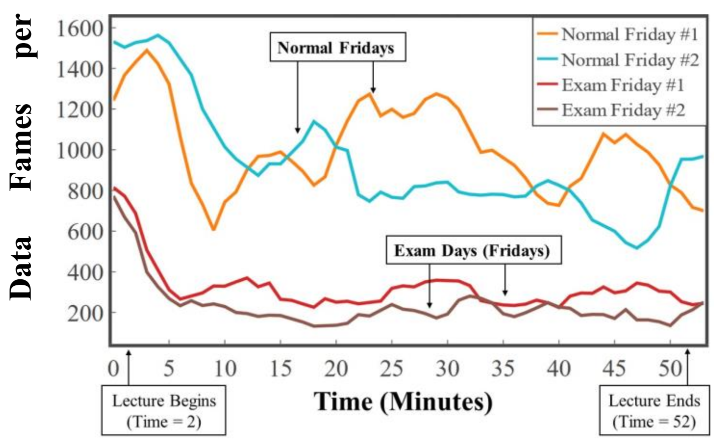


Figure 4-7: Comparison of Traffic Patterns on Exam Days and Normal Fridays

4.4.4. Spatial Analysis of Generated WiFi Traffic

The proposed system has the capability of separating collected traffic into spatial classroom divisions (i.e. left and right). This capability is demonstrated during one of the lectures where a short eight-minute quiz was distributed according to a specific procedure. The quiz procedure was as follows:

- The quiz was distributed to the right half of the classroom, simultaneously, the left half of the classroom was instructed to browse on their mobile devices.
- After 8 minutes, the quiz was collected from the right half followed by the distribution of the quiz to the left half of the classroom. During this time, the right side is instructed to browse on their mobile devices. After another 8 minutes the quiz is collected and the lecture resumes.

Using the RSSI Cutoff Values (RCV) determined during the SEMINAR set-up procedure, as discussed in Section 4.3, we divide the traffic into *left side* and *right side* based on the RSSI value observed from the left edge monitor (Figure 4-3b). Figure 4-8 displays the traffic pattern for both sides. Time intervals in which the different actions take place are shaded in Figure 4-8 and are labeled as: *Right-Side Quiz Distribution*, *Right-Side Quiz*, *Right-Side Quiz Collection and Left-Side Quiz Distribution*, *Left-Side Quiz*, and *Left-Side Quiz Collection*. It can be observed that during the Right-Side quiz the traffic intensity from the right side is much lower than that of the left side. Similarly, during the Left-Side quiz the traffic intensity of the right side is much higher than the left side. The proposed system effectively separates traffic generated by different sides of the classroom. Although there are noticeable differences in traffic intensities during each quiz interval, similarities can be observed during both the beginning and end of the lecture. Figure 4-9 displays the amount of traffic generated by each side during both quiz intervals. While the total volume of traffic generated by each side throughout the entire lecture is nearly equivalent, during respective quiz intervals, each side displays a dramatic decrease in traffic generation.

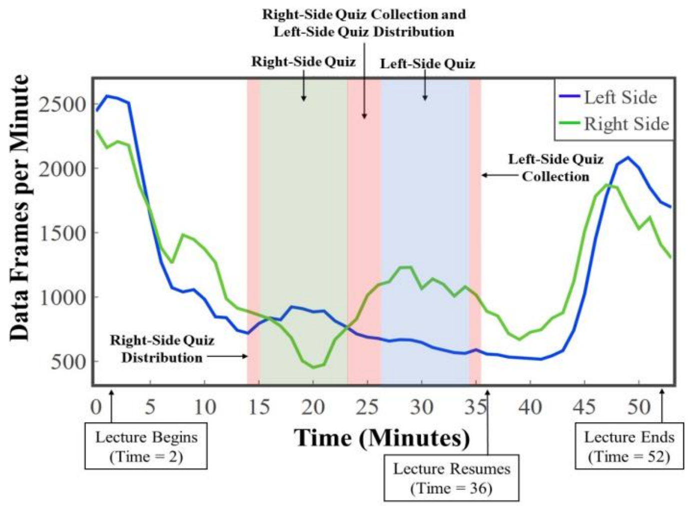


Figure 4-8: Spatial Traffic Analysis During Explicit Browsing Sessions

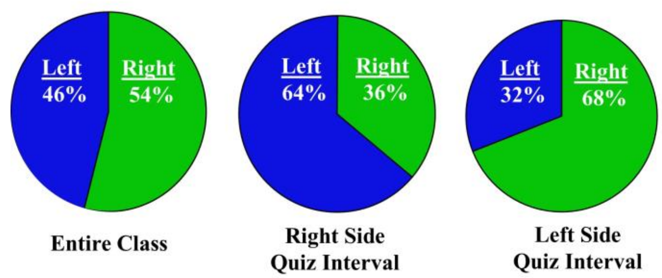


Figure 4-9: Proportion of WiFi Traffic Generated During Quiz Intervals

4.5. Future Work

Currently, we are extending the SEMINAR dataset by collecting data from a variety of courses. The courses being monitored have diverse class attributes (e.g. course level, given course material versus no given course material, etc.) which will be used to identify similarities and differences in mobile device usage among all class types. SEMINAR can be effectively deployed in multiple classrooms, ultimately providing a large overview of mobile device usage during class lectures across the university. In addition, a collaboration with scholars specializing in pedagogy is ongoing to provide ground truth student engagement measures. This will ultimately ensure that the proposed system accurately reports the best estimate of student engagement levels in real-time. Lastly, improvements to the front-end of the system are currently taking place to provide the best user experience for instructors and university administrators. This includes a clean display of real-time data as well as easy access to previous data.

4.6. Conclusion

This worked investigated the usage of mobile devices inside a classroom during a class lecture using the proposed SEMIANR system. Presented in this work is ability to use the proposed system to capture different device usage patterns across different days, including exam days with no device usage which show a best-case scenario of maximum engagement from the perspective of WiFi traffic measurements. Also presented are explicit browsing sessions that demonstrate the responsiveness of the system and. The system can be used to monitor device usage inside classrooms with the goal of using the data to determine a collective assessment of the engagement of students during lectures. We believe that this works opens doors to high frequency engagement measurements, ultimately providing an extensive student engagement dataset that can be used to provide quality of education or quality of teaching assessment. In the next chapter, we investigate a CSI-based activity recognition system that extends contactless exercise activity monitoring.

5 Human Activity Analysis by Exploiting WiFi Channel State Information

In this chapter, we present a system that exploits the ubiquitous WiFi signals and the correlations between signal changes and body movements to achieve contactless human exercise activity recognition. There is a growing trend for people to perform regular workouts in home/office environments because of the widespread understanding of physical and mental health benefits regular physical fitness brings. Additionally, there is an increasing trend to monitor these workouts in a contactless fashion, free from intrusive and cumbersome wearable devices. To aid contactless monitoring of exercises, this chapter presents a non-invasive system that recognizes exercise activity and provides fine-grained repetition counting information of each exercise set using WiFi channel state information. Different from prior works, we attempt to accomplish accurate exercise recognition while giving a higher priority to easy practical system deployment than typical done. In particular, our system aims to detect the desired exercise with a Tx-Rx device placement representative of real-world deployment, contrary to standard configurations in relevant literature. Since a single workout session typically consists of multiple sets of repetitions, it is imperative to be able to detect other non-exercise activities as well. Extensive data collection is performed to sufficiently train and validate machine learning classifiers. We present a novel approach to effectively extract exercise information embedded in received packets during the exercise and obtain both detection accuracy of pushup exercise and repetition count accuracy above 90%. Experiments show that exercise recognition can successfully be achieved by exploiting WiFi CSI with a more flexible device configuration that current relevant works.

5.1 Introduction

Extensive health studies [61-63] have shown that excessive sedentary behavior and physical inactivity are major risk factors for obesity, diabetes, and several cardiovascular diseases. Fortunately, works such as [64] and [65] have investigated strategies that are most effective to motivate behavior change among sedentary adults and indicate that physical activity monitors motivate physical activity and decrease sedentary behaviors. Therefore, reduction in such risk factors can be achieved by incorporating physical activity monitoring into a person’s lifestyle. Wristband wearable devices such as Apple Watch [66] and Fitbit [67] have been developed to promote healthy lifestyles. Other exercise activity monitoring solutions, such as [68], incorporate accelerometers and other motions sensors that are attached to the body in the form of wearable devices. A RFID-based solution is proposed in [69] to accomplish exercise recognition. While effective, all previously mentioned work requires the use of a wearable device to monitor user activity and therefore are inherently limited with respect to the total amount of activity monitored as the users may forget to attach device. Users may also find the use of a wearable devices while exercising uncomfortable and would rather opt out. A more desirable approach would be contactless recognition of workout activities. Ubiquitous WiFi infrastructures in home/office environments makes WiFi a reasonable sensing measurement to accomplish the goal of exercise recognition in a contactless fashion. In fact, WiFi channel state information has proved to be an effective sensing modality to accomplish contactless exercise activity monitoring and recognition of many bodyweight exercises as demonstrated in a variety of recent work as discussed in Related Work, Chapter 2.

While current CSI-based exercise activity recognition systems successfully achieve recognition of their various free weight and bodyweight exercises we find that current literature has a standard convention of Tx-Rx placement and orientation. Placement and orientation consist of a straight-line communication link between Tx and Rx 3m – 5m apart, and the human subject conducts exercise in the link. Although contactless, this setup is quite restrictive and can become a limiting factor in practical implementation in office/home environments since creating the Tx-Rx link requires sufficient space for both devices. In actual deployment of CSI-based exercise recognition systems, a desired setup is depicted in Figure 5-9. Home/Office WiFi Access Points (AP), typically in a fixed location on top of a desk or shelf, can serve as the Tx device. The Rx device can be placed in a designated workout area that the orientation of the Rx device is inconsequential to the exercise detection. Note the referenced setup is an unconventional configuration with respect to current literature as the Tx is placed in practical location resulting in nonequal distances from the ground. In addition, this configuration consists of device orientations where the antennas of the Tx and Rx devices are not directly facing each other. This setup is more representative of practical implementation of home/office contactless exercise monitoring systems.

Therefore, we aim to extend the current literature convention of restricted device placement and orientation when developing a system to detect or differentiate between various human exercises. In this work, we take contactless exercise recognition systems one step further by demonstrating that exercise data, namely the push-up exercise, can be accurately detected and analyzed to provide exercise statistics such as the number of pushup repetitions with an more practical device placement and orientation, different from current literature convention.

5.2 System Design

The proposed system entails several essential system functions required to achieve successful exercise recognition. Channel State Information measurements are collected in the form of a matrix that provides both phase and amplitude information of the incoming signal on each receive antenna. As discussed in Chapter 1, Orthogonal Frequency Division Multiplexing modulation scheme spreads the data across multiple frequencies creating multiple independent narrowband signals to be analyzed known as subcarriers. Each CSI stream contains readings from 56 subcarriers. Consequently, the CSI matrix contains data from all subcarrier frequencies, collected by each receive antenna, sent by each transmit antenna. In this work, we discard phase information as we are able to extract the necessary exercise information from the CSI amplitude information alone.

As illustrated in Figure 5-1, the raw CSI data from each collection set is processed through the system which contains two core system components. The first core component, the Pushup Data Classification (PDC) module, is tasked with identifying if the received signal data contains embedded pushup exercise information by the extracting 6 hand-crafted time-series features. Data which is successfully classified as 'pushup data' will be processed through the second core system component, the Pushup Data Repetition Counter (PDRC), tasked with detecting the number if pushups performed during the respective data collection.

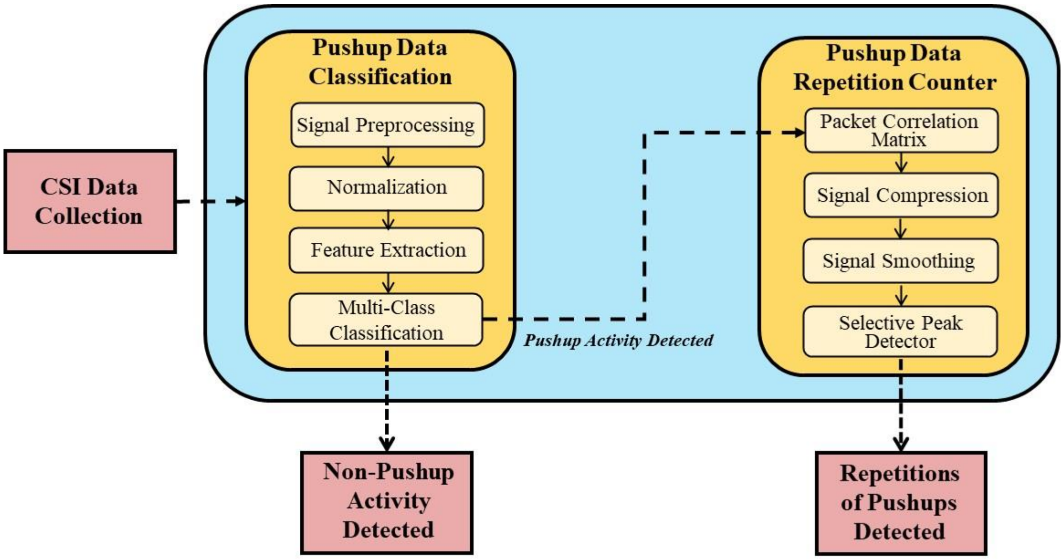


Figure 5-1: System Overview

5.2.1 Pushup Data Classification

Preprocessing and Normalization: The raw CSI amplitude measurements can be affected by external factors such as hardware imperfection of the commodity WiFi device, interference from nearby devices, as well as signal propagation properties of the ambient environment. Internal state transitions such as transmission rate adaptation and transmission power changes introduce burst noise in the CSI streams [70]. For an effective feature extraction, we preprocess the CSI amplitude data to remove any unwanted data outliers, noise, and trends. The proposed system analyzes the amplitude variance among subcarriers and antennas; therefore, we ensure that the calculated variance is not affected by any unwanted outlier amplitude values by applying a Hampel filter to remove outlier values. Specifically, we apply the Hampel filter with a sliding window at each subcarrier to remove the outliers which have significantly different amplitude values from other neighboring subcarriers. This filter effectively eliminates outliers and reduces signal noise. The CSI signals sometimes display a trend, which can be visualized as a positive or negative slope over the length of the signal. For this reason, we detrend the raw amplitude data by subtracting the mean amplitude value from each received packet in the current data collection set. Unity-based normalization is performed where all values are scaled into the range [0 1]. This step makes the system agnostic to specific subcarrier amplitude values observed from day to day or location to location and instead focus on the amplitude variation between subcarriers.

Data Classification: The data classification breakdown can be observed in Figure 5-2. The only desired data is the pushup data collection set. As shown, the collected data can be grouped into one of two high-level classes *Activities on Mat* and *No Activity on Mat.* Data can be further classified into four different classes. *Empty Room* data consists of CSI data collected when the data collection area is free from human subjects. *Lay Still* data consist of CSI data collected when human subjects laid on the workout mat with little to no movement. Various movements conducted on the workout mat such as, but not limited to, stretching, browsing on phone, and entering/departing collection area, are classified as *Misc. Movements* data. The final class of data is *Pushup* data where the data collection set contains embedded exercise information. While the pushup data is the only data of interest to be recognized, multiple data classes are needed to efficiently separate pushup data from other types of activity. We show in Figure 5-12 the benefit of constructing a binary classifier by combining outputs of the multi-class classifier. We apply the k-Nearest Neighbors algorithm (kNN) to classify the processed data. The multi-class classifier output is then converted to a binary output where one class is the *Pushup* Activity and the other is *No Pushup Activity*. Any data not classified as pushup activity is grouped into the *No Pushup Activity* class. Pushup activity data is then further analyzed by the PDRC.

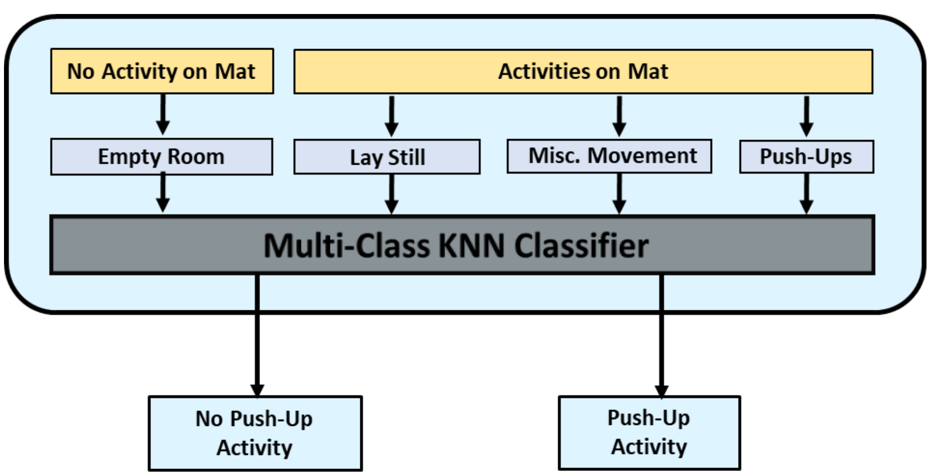


Figure 5-2: Classification Breakdown

Figure 5-3 displays the unique heatmap signatures of collected CSI data from different activities. The visual difference in the heatmap signatures help motivate our choice of extraction features.

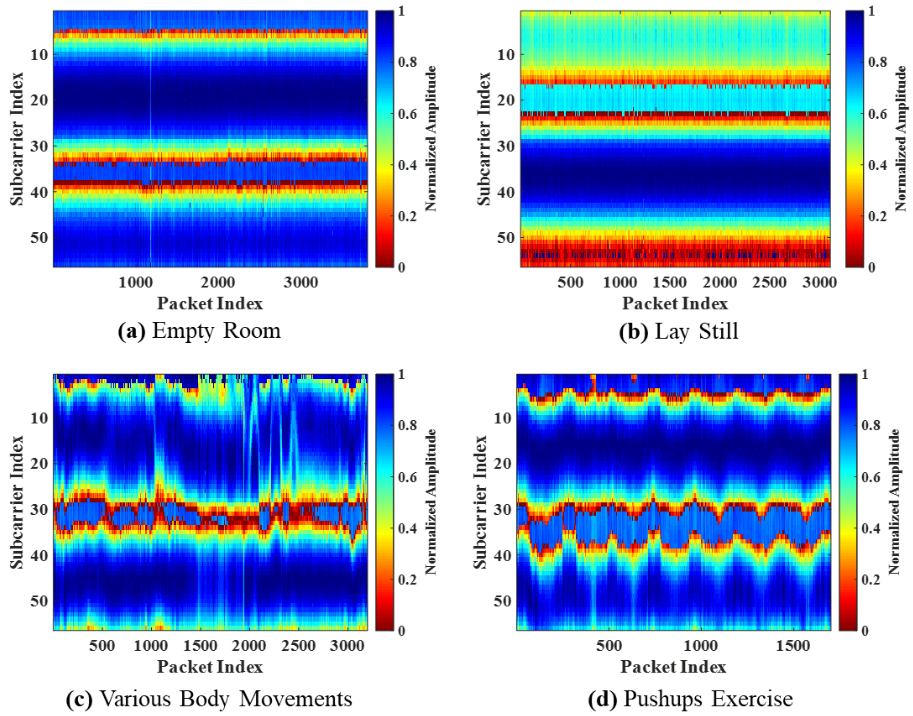
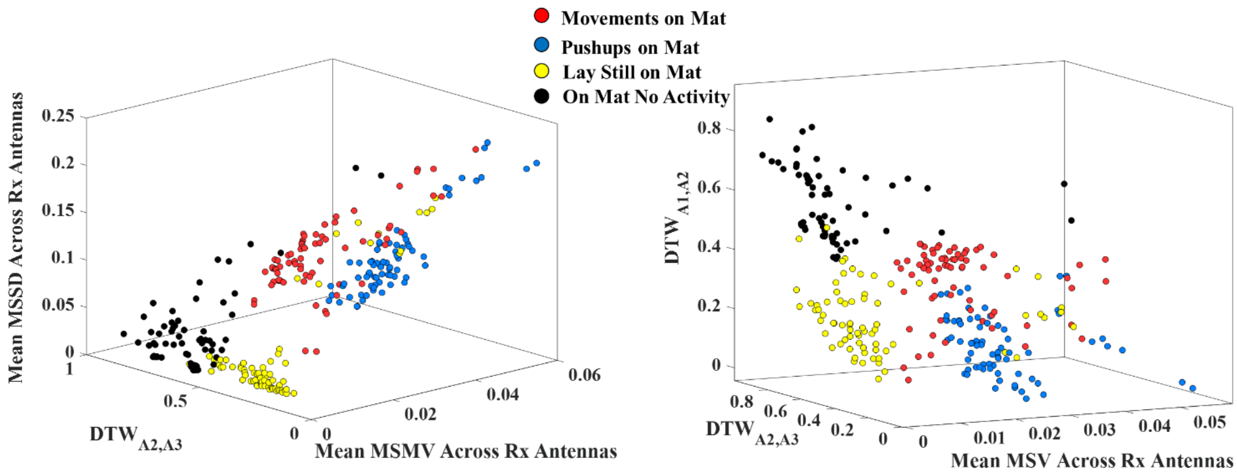


Figure 5-3: Heatmaps of Different Activities

<u>Feature Extraction</u>: We extract six hand-crafted features from each data collection set to construct a feature set for the classifier. Three features aim to extract the variation behavior between subcarriers, namely, *Mean Subcarrier Variance, Mean Subcarrier Standard Deviation, Mean Subcarrier Moving Variance* of each antenna. Three additional features aim to extract similarity measures between the three receiver antennas using Dynamic Time Warping (DTW). DTW is an algorithm used to measure the similarity between two data series. We measure the similarity of the signal received between each combination of two receive antennas. Since there are three possible combinations of the three receive antennas, we obtain three similarity measures to use as addition features. Figure 5-4 provides a visualization of feature separation due to the specified features. Figure 5-4a, 3 of the 6 features are used to illustrate the feature separation between the 4 classes. Specifically, the mean MSSD and MSMV across antennas, in addition to the $DTW_{A2,A3}$ similarity measure, were used. Fig 5-4b provides an additional perspective of the feature separation as

another 3 combination of features are used to illustrate separation in the different classes of data. Opposite from Figure 5-4a, this feature separation figure consists of two similarity measure features and one variation related experience. Classification results are presented in Section 5.3.1.



(a) Feature Separation Visualization #1 (3 of 6 features)

(b) Feature Separation Visualization #2 (3 of 6 features)

Figure 5-4: Feature Separation Virtualizations

5.2.2 Pushup Data Repetition Counter

The purpose of this module to extract workout statistics from the processed data collection set. Specifically, this module detects the number of pushups performed by the human subject by extracting out the periodic signal, created by human motion, that is embedded in the received signal.

Packet Correlation Matrix (PCM): The first step to extracting the repetition information out of the classified pushup data is to construct a packet correlation matrix. For each packet in the set, a correlation coefficient is determined for every other packet in the data collect set, effectively creating the correlation matrix. The idea behind this step is to exploit the stability and consistency of CSI amplitude values for a given location. Consider the pushup exercise sequence as shown in Figure 5-5. Given a receiver at a fixed nearby location collecting CSI data as discussed in Data Collection section, as a human subject completes the exercise sequence in Figure5-5 (a)-(e), we expect that majority of subcarriers will display similar amplitude values while in UP position (e.g. Figure 5-5a,c,e) and similar amplitude values while in DOWN position (e.g. Figure 5-5b,d), respectively.

(a) UP Position **(b)** DOWN Position **(c)** UP Position **(d)** DOWN Position **(e)** UP Position

Figure 5-5: Pushup Exercise Sequence

Figure 5-6 provides packet correlation matrices for 4 different pushups collect sets. Note that the data collection begins in the UP position as in Figure 5-5a. It can be observed that the PCM is able to clearly illustrate a periodic motion across time. Depicted in Figure 5-6a, specifically for packet indices 0 to 1000, is a group of subsequent received packets that are highly correlated with respect to subcarrier amplitude values for the initial 480 packets, approximately, indicated by the darker colors in the figure. To map that data to physical human movement, the initial 400 packets are highly correlate since the human subject is in the UP position, effectively creating a distinct consistent multipath signal. After roughly 400 packets, the next batch of received packets (e.g. approximately packet indices 401 through 550) began to correlate less with the initial batch of received packets. This data maps to when the human subject moves from the UP to DOWN position. A noteworthy observation from Figure 5-6 is the diversity in pushups performed. While Figure 5-6a shows six pushups performed at a near fixed rate, Figure 5-6c shows a pushup exercise session where the subject initially began fast and completed the last half of the set at a slower pace.

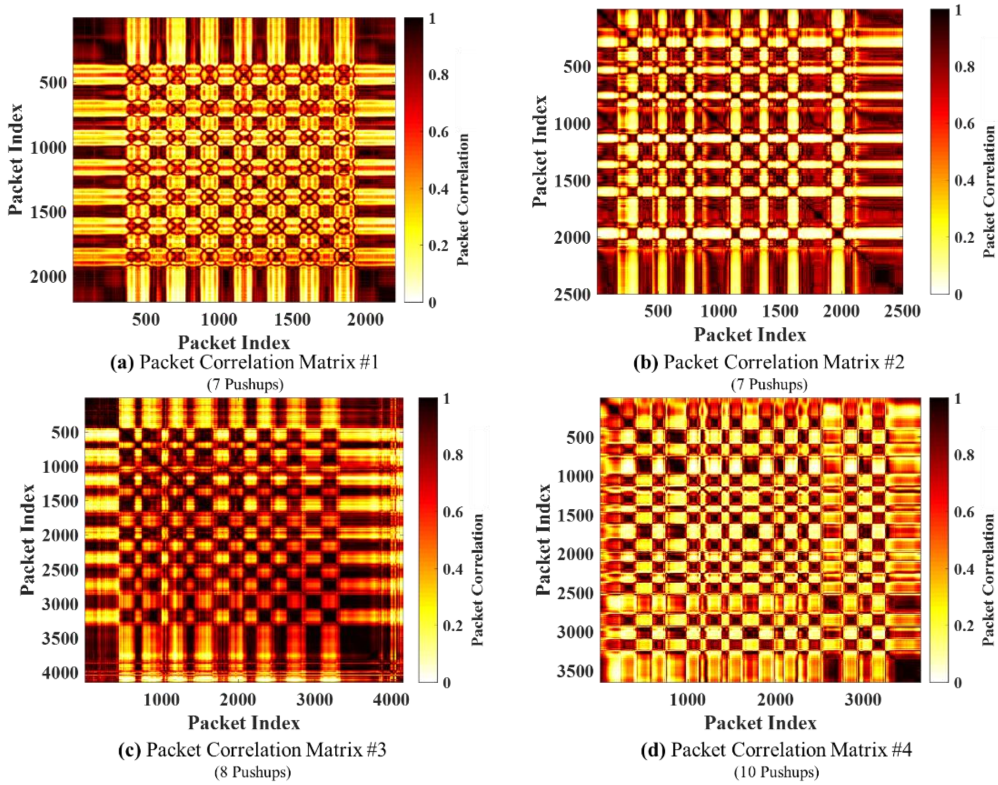
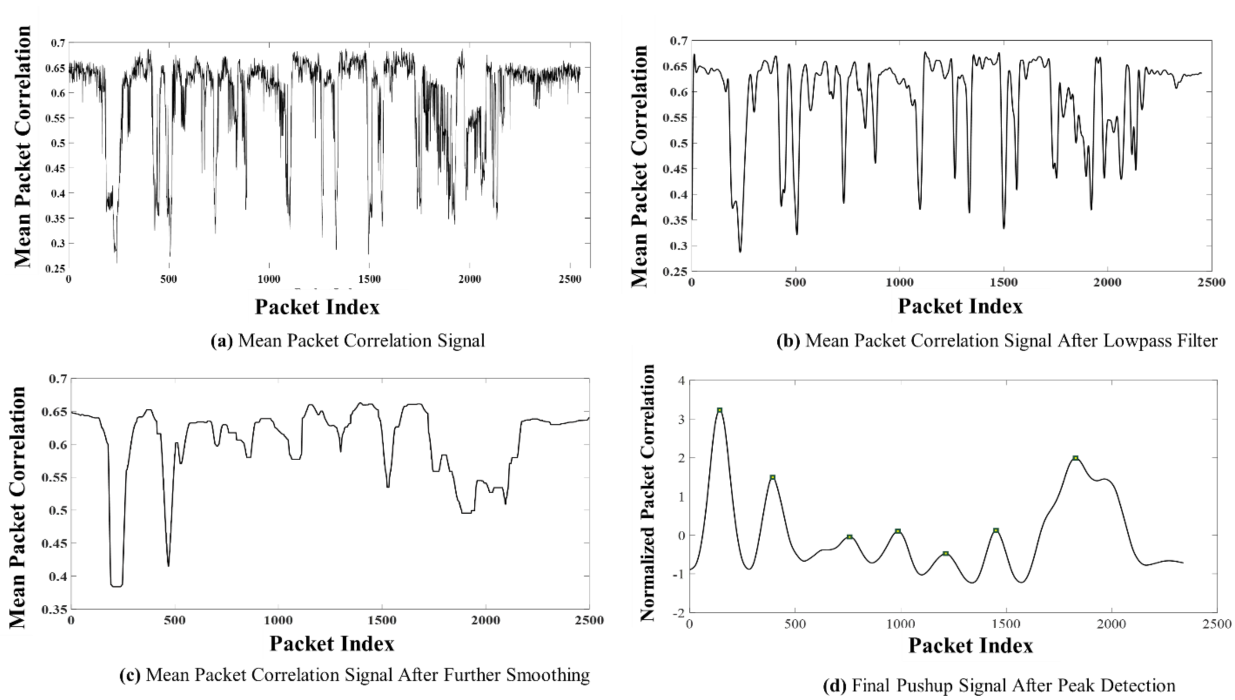


Figure 5-6: Pushup Data Packet Correlation Matrices

After the PCM is calculated, the mean signal is obtained by averaging all correlation values in each column of the matrix. The result, as displayed in Figure 5-7a, is the average packet correlation signal which encompasses the desired exercise information. This data is a continuation of Packet Correlation Matrix #1 in Figure 5-6a. Further processing is required to accurately detect the number of pushups performed. We implement a cascade of filters to clean the signal in preparation for the peak detector. First, a lowpass filter is utilized to discard unwanted high frequency noise and the resulting signal is displayed in Figure 5-7b. Next, a median filter is used to smooth the signal in order to obtain a rough outline of the period motion as the packet index increases from zero. This can be visualized in Figure 5-7c. The data is smoothed using Savitzky–Golay filter which computes the local polynomial least square fitting in the time domain to filter out noise while ensuring that the shape and width of the signal are unchanged. Thus, the Savitzky–Golay enables CSI signal denoising without distortion of the signal waveform. After a final moving average is implemented to eliminate any unwanted peaks in the signal, a peak detection algorithm is performed. As depicted in Figure 5-7d, the final signal is a periodic signal that represents the periodic human motion during the pushup exercise. A green box located on each peak illustrates successfully detected peaked in the signal. At this stage, the number of detected peaks will serve as the number of pushups performed. An additional entire detection process is provided in Figure 5-8.



(a) Mean Packet Correlation Signal

(b) Mean Packet Correlation Signal After Lowpass Filter

(c) Mean Packet Correlation Signal After Further Smoothing

(d) Final Pushup Signal After Peak Detection

Figure 5-7: Pushup Detection Counter Data Processing

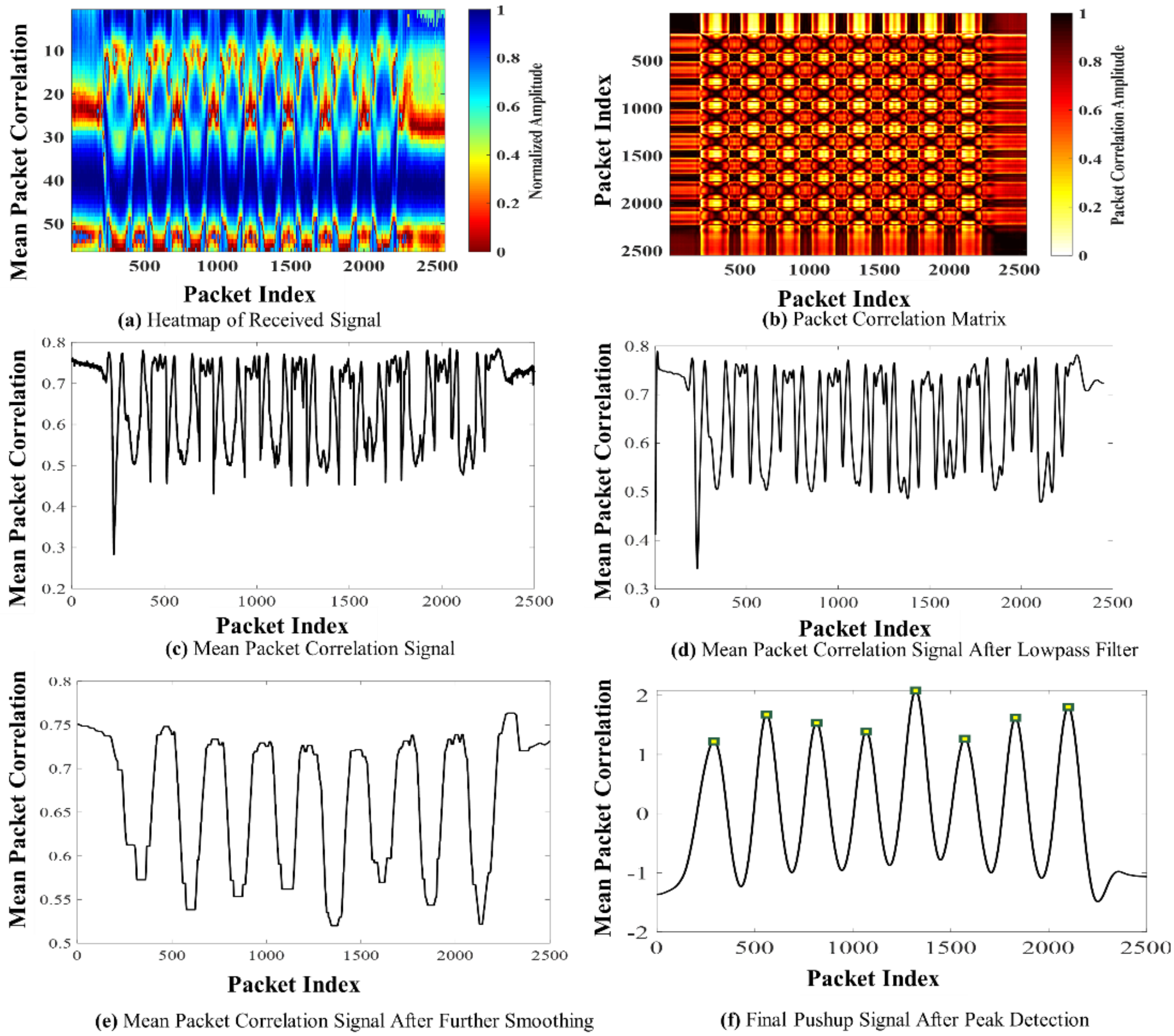


Figure 5-8: Full Pushup Detection Counter Data Processing

5.3 Evaluation

In this section, we present the implementation and evaluation results of the proposed exercise recognition system.

Hardware Setup. The proposed system incorporates two PCs running Ubuntu 14.04 LTS (64bit) with Linux kernel is 4.1.10. One device serves as the AP and Tx device and the second device serves as the Rx, as illustrated in Figure 5-1. Both devices have an Atheros AR9580 Network Interface Card (NIC) installed, modified using Atheros CSI Tool. Tx is equipped with two transmit antennas with a packet transmission rate of 200 packets per second. Rx is equipped with three receive antennas and continuously captures the incoming packets for later processing. As a result, we exploit the variation in CSI subcarrier values across the multiple receive antennas to extract pushup information.].

Environment and Data Collection. We consider a scenario where the human activities are monitored in multiple indoor environments using Tx and Rx devices discussed in previous section. Figure 5-9 illustrates an indoor home environment where Rx is placed on the ground in a designated exercise area while Tx, the AP, is located in designated work area on top of a desk. The unique aspect of our collection setup is the how Tx and Rx are separated in space. A standard Tx-Rx placement, as seen in many exercise recognition works, consists of both devices in the middle of the room on the floor. The subject will then conduct the exercise between the two devices. While effective, that standard placement can be a limiting factor in deployment of practical exercise monitoring systems. Consider an XYZ coordinate system, while current literature separates the Tx and Rx devices only on a single axis (e.g. x-axis, y-axis), the proposed system, however, is designed to be practical and flexible where the Tx-Rx devices may be placed with separation on all three axis. Figure 5-9 illustrates the separation in the x-axis (e.g. 4 meters), separation in the y-axis (e.g. 3.5 meters), and separation in the z-axis (e.g. 1 meter). We demonstrate that this unconventional data collection setup is does not impede our ability to obtain periodic exercise information.

One data collection consists of a 15-30 second session in which 1 of 4 human activities, discussed previously is being performed. The collected data is obtained from 7 participants, each conducting multiple data collections effectively creating 500 total collection sets of activity data. Pushup collection sets consisted of pushups ranging from 5 to 12 repetitions per set. When performing pushups, the subject begins in the 'UP' position and when the specified number of pushups are completed, the subject ends in the 'UP' position at which point the data collection ends.

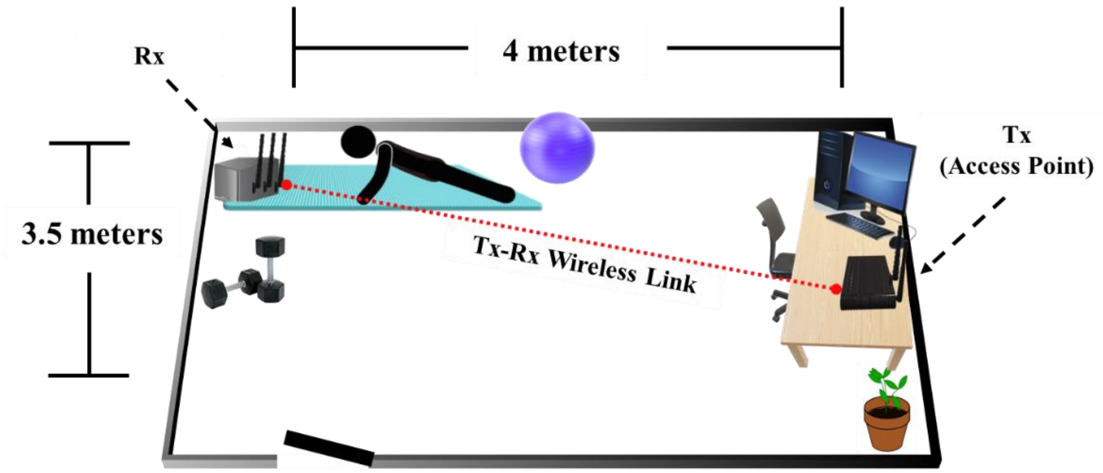


Figure 5-9: Data Collection Environment and Device Placements

5.3.1 Pushup Data Classification

In this section, we evaluate the pushup data classification performance. To evaluate the performance of our classification system we use three evaluation metrics, k-fold cross validation, confusion matrix, and accuracy. k-fold cross validation splits the dataset into k smaller sets and a model is trained using k − 1 of the folds and validated on the remaining part of the data. In our implementation k = 10. We ensure robust training by mixing and shuffling the collections from all participants on different days. It is important to recognize that due to subtle changes in the static environment, data from the same participant may exhibit less consistency. Therefore, we use the diverse data collected to train a kNN model with Euclidean distance metric and number of neighbors equal to 6. After 10,000 runs, the average cross validation loss reported was .0473. Figure 5-10 displays mean confusion matrices calculated after 10,000 runs. Initially, a multi-class classification is performed. This step benefits our overall objective of separating pushup activity data from all other classes of activity data when on the workout mat. The full set of non-pushup activities have both similar and distinct features. It proved advantageous to group the different kinds of non-pushup activities by exploiting their distinct features, for an initial layer of classification. Figure 5-10a displays the confusion matrix of the multi-class classification performance. All 4 classes can be distinguished with an accuracy greater than 85%, three of which above 90%. Most importantly, the system detects approximately 95% of all pushup data. Although the non-pushup activities are not of interested in the current work, the ability to classify the other activities while on the workout mat aids the long-term system design objective discussed in Future Works section.

Actual Class

Predicted Class	No Activity on Mat	Lay Still	Body Movements	Pushups
No Activity on Mat	**96.94%**	4.60%	2.9%	.18%
Lay Still	1.75%	**91.4%**	1.57%	.92%
Body Movements	1.03%	2.94%	**85.6%**	4.36%
Pushups	.28%	1.06%	9.93%	**94.53%**

(a) Confusion Matrix of Multi-Class Classification Performance

Actual Class

Predicted Class	Non-Pushup Activity	Pushups
Non- Pushup Activity	**95.41%**	5.46%
Pushups	4.59%	**94.54%**

(b) Binary Confusion Matrix of Push Data Classification Performance

Figure 5-10: Confusion Matrix for Pushup Data Classifier Performance

Since there exists exactly one data class of interest, the task of filtering non-pushup activity data collection sets is effectively a binary classification problem. Figure 5-10b provides the binary confusion matrix after converting multi-class results to binary. Similar to the positive detection performance of pushup activity, the system classifies 95.41% if non-pushup activity correctly. It should be noted that while the system incorporates an additional classification step, the outcome is an increased detection accuracy. As shown in Figure 5-11, when using the same six features to directly construct a binary classifier where the two classes of data are *non-pushup activity* and *pushup activity*, the overall performance is desirable. Pushup and non-pushup data are detected with approximately 90% and 96% accuracy, respectively. While pushup detection accuracy of pushup data is 90%, the pushup data detection accuracy via multi-class classification achieved a higher detection accuracy of nearly 95%. Not only is the 95% total accuracy of the binary classifier after multi-class output conversion higher than that of the 93% total accuracy native binary classifier, as displayed in Figure 5-12; the native binary classifier is less desirable simply because the amount of pushup data loss when moving to next stage in the exercise recognition system is greater. As a result, the proposed system implements a multi-class classifier and converts its outputs into a binary classification problem.

Actual Class

Predicted Class

	Non-Pushup Activity	Pushups
Non- Pushup Activity	**95.96%**	9.83%
Pushups	4.04%	**90.17%**

Figure 5-11: Confusion Matrix for Pushup Data Classifier Performance without Multi-Class Outputs

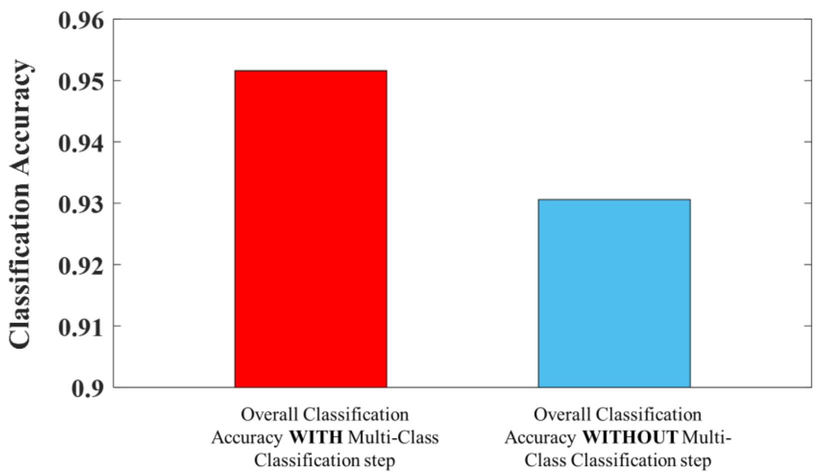


Figure 5-12: Classifier Performance

5.3.2 Pushup Repetition Counter

In this section, we evaluate the pushup data classification performance. We thoroughly evaluate the performance of the proposed pushup repetition counter by considering the following evaluation metrics:

<u>*Pushup Repetition Precision*</u> $\frac{TRC}{N_R} = PRP$, where TRD is the total number of repetitions detected by the system and N_R is the actual total number of pushup repetitions from all collection sets. This accuracy reflects the overall ability of the system detect a pushup repetition when given a pushup repetition and provides reliability assurance.

<u>*Perfect Repetition Count Accuracy (PRCA).*</u> $\frac{PS}{N_{PU}} = PRCA$, where PS represents the number of 'perfectly' detected sets, where the estimated number of repetition and match the expected number of repetitions for a particular set. N_{PU} is the total number of pushup collection sets. The $PRCA$ value should be as high as

possible since *PRCA* reflects the ability of the system to detect all pushups performed by a user during data collection set.

Imperfect Set Repetition Error (EPRE). *EPRE* is the expected set repetition count error. This error value provides the expected difference in the number of repetitions detected by and the actual number of repetitions performed per data collection set. This evaluation metrics looks at how much the detected repetition count is expected to differ from the actual count per set given that the set did not report the current number of repetitions.

End-to-End Repetition Pushup Repetition Precision (EPRP) *EPRP* is the pushup repetition count precision after the data is processed end-to-end. This means that *EPRP* depends on the systems ability to correctly classify pushup data as pushup data and non-pushup data as non-pushup data.

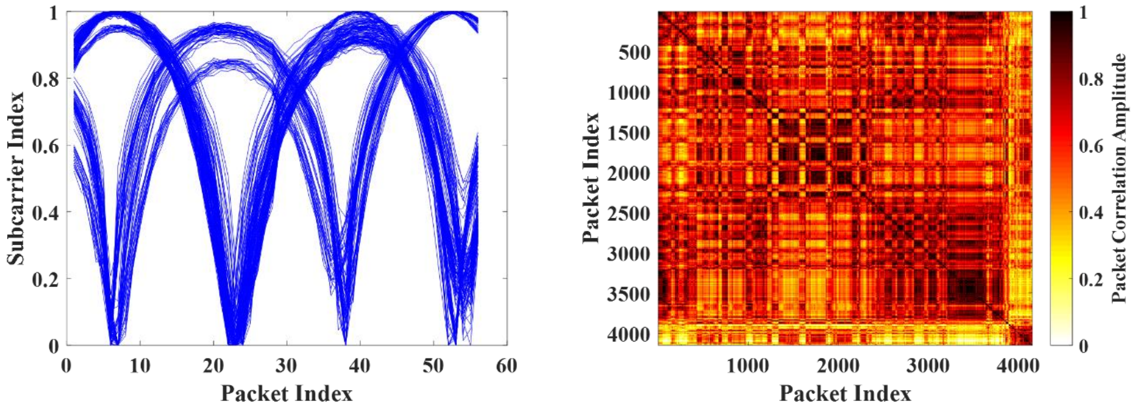
Table 5-1 provides the performance results obtained from experimental analysis. The pushup repetition precision is 98.24%. This demonstrates that the proposed system is able to accurately count the number of repetitions performed while using the proposed device placement framework. We also calculate the *PRCA.* The proposed system detects the correct number of pushup repetitions in 92% of the pushup collect sets it encounters and when the detected number of repetitions in not correct is off by ± 1.08 repetitions. The aforementioned results were with respect to the pushup detector as a stand-alone mechanism. We additionally provide end-to-end performance results where for a pushup repetition to be successfully detected, the data collection set must first be classified as pushup data. The end-to-end pushup repetition precision is 96%. This is only slightly less than the expected 98% of the pushup repletion counter and means that the pushup data classifier effectively pushes through to repetition counter only pushup data, while minimization other activity data. Since there is a small amount of non-pushup activity that gets passed through, the overall repetition count error expected per set when the repetition count was not perfectly detected is ± 2.92 repetitions.

Table. 5-1: Pushup Repetition Counter Performance

Evaluation Metric	Value
Pushup Repetition Precision	98.24%
Perfect Repetition Count Accuracy	92.4%
Imperfect Set Pushup Repetition Error	± 1.08 Repetitions
End-to-End Pushup Repetition Precision	96.17%
Overall Pushup Set Repetition Error	± 2.92 Repetitions

5.4 Limitation

It should be noted that the pushup repetition counter module performance suffers when encountered with a problem scenario. In complex environments, multiple multipath CSI signatures can be received within a very short time window. Figure 5-13a illustrates this phenomenon. Some collection environments are inherently rich in multipath. When faced with this situation, the packet correlation matrix constructed as in Section 5.2.2, does not provide an accurate depiction of the periodic human motion during the exercise. This is a natural effect of receiving multiple signatures because two different received CSI signatures may already be unique, thus the change in correlation values in the data does not solely contain variation information caused by human movements. The negative effect of multiple signatures with respect to the packet correlation matrix can be viewed in Figure 5-13b. When compared to packet correlation matrices discussed in Section 5.2.2 the pushups in Figure 5-13b are less distinguishable. As discussed in Future Work, we aim to extend system capabilities, including the ability to overcome multiple signatures obtained from complex wireless environments in which the aforementioned phenomenon is extensively investigated. Currently, in this work we report repetition detection results after discarding collections with multiple signatures.



(a) Multiple CSI Signatures from Pushup Data Collection
(6 Pushups)

(b) Corresponding Packet Correlation Matrix
(6 Pushups)

Figure 5-13: Multiple CSI Signatures

5.5 Future Work and Discussion

Our plan to extend the current work involves several components.

System Robustness. As discussed in section 5.4, currently system is not robust in the event of sever multipath effect and multiple CSI signatures are present in the collected data. We most incorporate further processing to effectively separate the signatures. It can be seen in Figure 5-13a the when multiple signatures are formed, each CSI signature is generally consistent, therefore, some clustering method can be used to distinguish which packets are associated with which signatures. This is important since each signature contains exercise information embedded within. Additionally, we will have to ensure that while analyzing the individual signatures that the overall exercise time-related information is preserved for later exercise statistics extraction. Given that our objective is practicality, we must ensure the system is robust in different real-world scenarios and settings. For example, there could be multiple persons or other moving objects around. The person or other objects could block the direct path between the transmitter and receiver; or the person can be moving in the vicinity of the exerciser during the workout, which could affect the recognition accuracy of the system.

Multi-Person Workout Sessions. Although the proposed system is designed for a single person, a real-world scenario can consist of multiple users conducting exercise together as shown in Figure 5-14. Since the received signal at each receiver is independent, each Rx device should be able to extract nearby exercise data, unaffected by the exercise movements of another person. Initial experiments support our hypothesis that we can obtain individual workout statistics with the device placement in Figure 5-14. Note, that the device placement is an extension of the currently proposed device placement. We plan to systematically analyze and model system parameters such as the minimum distance required between two neighboring exercising subjects.

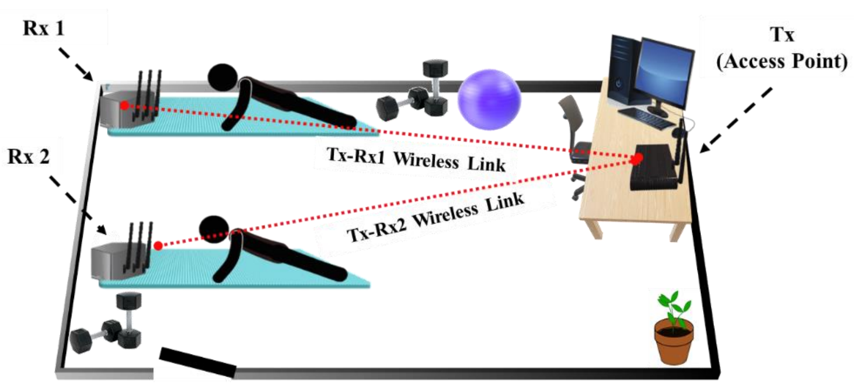


Figure 5-14: Multi-Person Workout Scenario

Multi-Exercise Recognition System. Related works such as [71-72] show that it is possible to classify various exercises (e.g. pushups, sit-ups, and squats). This was not the objective of the proposed work, however, to confidently claim and demonstrate that the proposed device placement and any other similar practical setup can achieve same performance as state-of-the-art cumbersome device placement, we must incorporate a multi-exercise classifier.

In addition, we plan to add to the list of workout statistics provided. Currently, we provide only repetitions detected. We can add abilities such as measuring the time interval between each workout activity or assessing if the exercises were performed properly. Altogether, consider group exercise classes where individuals must remain in their provided workout space and follow the instructions of the workout instructor. A small Rx device can be placed nearby, and the workout analysis can be provided, and even compared to the instructor's performance.

5.6 Conclusion

In this work, a contactless exercise recognition system exploits the unique variations in the wireless channel state of individual wireless receivers caused by nearby human movements was proposed. More specifically, we proposed a system that employs various signal processing techniques to extract out the nearby cyclical human movement information embedded into the received wireless signals, ultimately providing contextual information for specific human exercise activities. The collected data cannot directly be used to obtain fine-grained activity information, so we design a series of data denoising and smoothing methods prior to extracting hand-crafted features to distinguish pushup data from the other classes. Ultimately, the proposed system can confidently perform fine-grained exercise recognition, namely the pushup exercise, and provide exercise statistics such as the number of sets and repetitions without the need of wearable device.

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