Wi-Chase: A WiFi based Human Activity Recognition System for Sensorless Environments

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***Abstract*—An extensive set of research efforts have explored Channel State Information for human activity detection. By extracting CSI from a sequence of packets, one can statistically analyze the temporal variations embedded therein and recognize corresponding human activities. In this paper, we present Wi-Chase, a sensorless system based on CSI from ubiquitous WiFi packets for human activity detection. Different from existing schemes utilizing only CSI of one or a small subset of subcarriers, Wi-Chase fully utilizes all available subcarriers of the WiFi signal and incorporates variations in both their phases and magnitudes. As each subcarrier carries integral information that will improve the recognition accuracy because of detailed correlated information content in different subcarriers, we can achieve much higher detection accuracy. To the best of our knowledge, this is the first system that gathers information from all the subcarriers to identify and classify multiple activities. Our experimental results show that Wi-Chase is robust and achieves an average classification accuracy greater than 97% for multiple communication links.**

***Index Terms*—Channel state information, Sensorless sensing, Activity recognition, Machine learning.**

I. INTRODUCTION

Human activity detection has gained tremendous momentum in recent years, particularly in the face of expanding reach of cyber physical systems. Traditionally, it is accomplished by using dedicated sensors [1]. These sensors need to be attached to a human body or be placed on an interactive object [2]. However, owing to the potential inconvenience and high cost, device free human activity recognition has recently attracted a plethora of research efforts. These range from vision (camera) based activity detection [3] to radio frequency (RF) based detection systems [4].

Due to its ubiquitous presence with deployed infrastructures, WiFi signal is among the first to be employed for human activity detection purposes. For example, received signal strength indicator (RSSI) of WiFi signal is employed in [5] toward this end, as RSSI exhibits signal perturbations as a single amplitude that varies significantly in case of an activity. Although RSSI can obtain fair detection accuracy, it experiences severe performance degradation in complex environments due to temporal variations, signal reflections and phenomenon like fading [6]. This limits RSSI only suitable for coarse level applications as it may increase, decrease or even remain unchanged based on the link quality and obstacles between the WiFi access point and the activity body [7]. Fortunately, with recent advancement and availability of advanced tools in 802.11n, it has become possible to collect fine level channel state information (CSI) from commodity WiFi devices. As CSI is a complex value containing subcarrier-level channel measurements, it enables a broad range of ubiquitous sensing applications to exploit these detailed channel perturbation over WiFi signals for finer level activity detection.

Indeed, an extensive set of research efforts have explored CSI to design sensorless sensing systems [8]–[10]. By extracting CSI from a sequence of packets, one can statistically analyze the temporal variations embedded therein and recognize corresponding human activities. Moreover, it can also serve as critical parameter in uncovering any abnormal behavior for a specific environment, including elderly and in-home infant surveillance, health care with emergency responses, intrusion detection and industrial automation [11], [12].

In this work, we present Wi-Chase, a sensorless system based on CSI from WiFi packets for human activity detection. *Different from existing schemes utilizing only CSI of one or a small subset of subcarriers, Wi-Chase fully utilizes all available subcarriers of the WiFi signal and incorporates variations in both their phases and magnitudes*. Specifically, Wi-Chase employs subcarrier level majority voting that can identify much finer level activities with higher accuracy. Our contributions in this paper can be summarized as following.

- We present Wi-Chase system architecture to detect and classify multiple human activities. We design an adaptive Activity Detection Algorithm (ADA) that evaluates the variations in all the subcarriers of a received packet. We propose that each subcarrier carries integral information that will improve the recognition accuracy because of detailed correlated information content in different subcarriers. To the best of our knowledge, this is the first system that gathers information from all the subcarriers to identify and classify an activity and therefore achieves high detection and classification accuracy.
- We propose majority voting at the subcarrier level to classify an activity. Additionally, we employ both amplitude and phase features in our system. These coupled together allow us to achieve much higher classification accuracy as compared with other related works using only amplitude or phase features with a small subset of subcarriers.
- We construct a diverse dataset of activities from distinct users. Using this dataset, we analyze our system for varying number of subcarriers and T_x-R_x communication links in order to achieve high accuracy. The results obtained confirm that Wi-Chase achieves an average accuracy greater than 97% for multiple communication links.

A. Related Work

Growing interest in sensorless activities detection has attracted both research and industry community towards CSI analytics. Related CSI based applications vary from coarse activity detection such as Wi-Vi [13], WiTraffic [14] to fine activity recognition systems like Wi-Track [8], Wi-Sleep [11] and Wi-See [12]. In [15], researchers have presented a phase based system that employs statistical variations of mean and

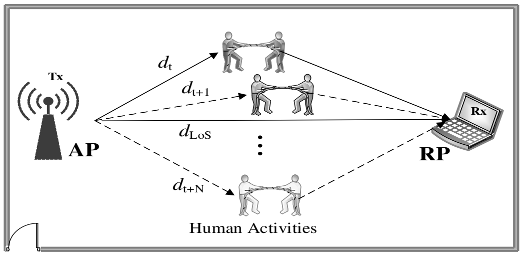


Fig. 1. WiFi signals reflection scenario.

standard deviation to differentiate between static and dynamic environments. Our work improves the accuracy by using integrated (amplitude and phase) features that can identify activities to finer level. Rather than identifying a single walking activity as presented in [16], our proposed system is capable of accurately classifying different activities. In [17], APSense is proposed that uses CSI to sense different hands movements. However, they use predetermined window to continuously check for any activity. This is time inefficient and yields relatively low accuracy. Additionally, they use only amplitude based information to differentiate between different hands movements. Wi-Chase avoids predetermined time window and exploits variance among all the subcarriers alongwith subcarrier level majority voting to achieve high classification accuracy. Unlike Wi-Sleep [11] that employs only a subset of subcarriers, we show that utilizing all the subcarriers improves the classification accuracy of our system.

The rest of this paper is organized as follows. In Section II, we provide CSI background and radio propagation model. The system model of Wi-Chase is described in Section III. The methodology used and different modules of Wi-Chase system is discussed in Section IV. The experimental settings and performance evaluation is presented in Section V. In Section VI we conclude the paper with some highlights on future work.

II. CSI Overview and Propagation Model

Wi-Chase leverages Channel State Information (CSI) based PHY layer information to sense and classify human activities, fully exploiting IEEE 802.11n/ac with MIMO supported by most existing WiFi devices. In 802.11n/ac, each MIMO link, using OFDM technology, comprises of multiple subcarriers, each of which possesses individual channel frequency response characterized by the CSI. Fig. 1 is an illustration of human activities, coupled with normal radio frequency reflections and multipath interference, resulting in temporal and spatial changes of the CSI of the subcarriers.

Let N_T represents the number of transmission antennas and N_R represents the number of receiver antennas. If $\mathbf{X}_i$ and $\mathbf{Y}_i$ represents the transmitted signal vector and received signal vector for any packet i, then for a MIMO system the received signal can be expressed by the following equation

$$\mathbf{Y_i} = \mathbf{H_i}\mathbf{X_i} + \mathcal{N}_i \quad i \in [1, N], \tag{1}$$

where $\mathbf{H_i}$ represents the CSI matrix for a packet i, $\mathcal{N}_i$ is the white Gaussian noise and N shows the number of correctly received packets.[1] Consequently, for one spatial link between a single transmit-receive antenna pair, we can write CSI matrix as

$$\mathbf{H} = [h_1, h_2, \cdots, h_{30}] \quad i \in [1, N]. \tag{2}$$

This implies that we obtain $N_T \times N_R \times 30$ CSI values for each packet to be analyzed. In Eq. (2) each h_i is a complex value embedding information about the amplitude and phase of the subcarrier that can be expressed by the following equation

$$h = \mid h \mid e^{j \sin \theta}, \tag{3}$$

where $|h|$ and θ are the magnitude and phase respectively.

Perturbation introduced by human activities toward CSI is heavily coupled with the radio propagation model. In this paper, we assume there is a Line of Sight (LoS) path d_{LoS} and multiple scattered paths d_{t} at time t. The LoS path experiences free space path loss and the power received by the receiver placed at a distance d from the transmitter can be described by Friis equation [19] incorporating signal reflection and path length due to human activity [20] as

$$P_R(d) = (\frac{\lambda}{4\pi})^2 (\frac{1}{d^2 + 4h^2 + \delta^2}) G_T G_R P_T, \tag{4}$$

where h is the perpendicular distance from the point of reflection to LoS path, δ takes into account the reflections and corresponding path length caused by any human activity in the surroundings, λ is the signal wavelength while G_T and G_R are the transmitter and receiver antennas gain. P_T is the power of the transmitted signal. Any human activity will constitute multiple reflection paths and will cause different path lengths that will vary the received power. For static environment, P_R and channel state are relatively stable. However, human activities will cause proportional changes in the channel state and P_R because of multipath fading and signal reflections. This results in high variance in CSI matrix and P_R that can be employed for activity recognition in our design of Wi-Chase.

III. System Model

Wi-Chase exploits the variance in CSI of multiple subcarriers to detect any activity in received packets. Toward this end, in our model, CSI matrices are analyzed using Activity Detection Algorithm (ADA). Anomalous CSI data is then used to extract characteristically unique features to be used for learning. More specifically, numerous magnitude and phase features are used to construct training data, which is used together with machine learning algorithms and subcarrier level majority voting to classify new activities of a subject. Fig. 2 illustrates the overall architecture and process of the proposed system.

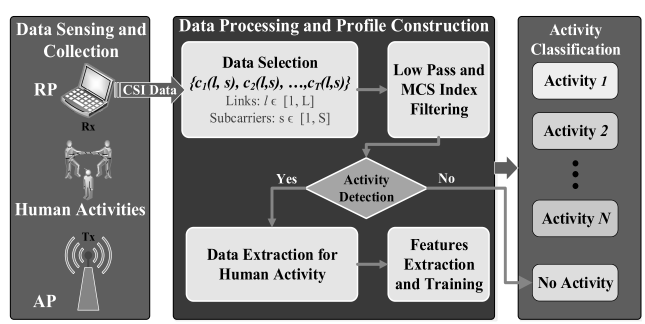


Fig. 2. System architecture of Wi-Chase.

[1]In our experiment, we extract these CSI matrices for each transmit-receive antenna pairs using a tool designed to be used with Intel 5300 WiFi NIC [18]. It reports CSI values for thirty subcarrier groups evenly spread in 20 MHz channel over 56 subcarriers.

Wi-Chase comprises of three major stages, *Data Sensing and Collection* phase, *Data Processing and Profile Construction* phase, and *Activity Classification* phase. In data sensing and collection phase, Wi-Chase establishes a communication link between the transmitter and the receiver to get the physical layer information of the surrounding environment. In our experimental setup, we simply employ an existing WiFi Access Point (AP) to act as a transmitter, whose continuously transmitted beacon packets are received by a laptop as Receiver Point (RP) for collecting and processing.

The next phase of data processing and profile construction consists of five modules, namely *CSI Data Selection*, *Low Pass (LP) and Modulation and Coding Scheme (MCS) Filtering*, *Activity Detection*, *Data Extraction for Human Activity* and *Features Extraction and Training*. The *CSI Data Selection* module extracts CSI for all T_x-R_x antenna pairs of received packets at subcarrier level. The LP and MCS filtering uses Butterworth low pass filter to remove noise from collected CSI data. This is an integral step as it filters embedded noises generated by environment temperature, humidity, sound, etc. Activity detection module utilizes our proposed algorithm to detect variance in the subcarriers of consecutive packets to identify activity patterns. For any activity identified, we extract the CSI values and define unique features to construct training data through the Features Extraction and Training module.

The activity classification phase processes the new data to detect any human activity along with the profiles of activities from the previous stage to classify new data. Wi-Chase employs k-Nearest Neighbor (kNN) [21] and Support Vector Machine (SVM) [22] based machine learning classifiers for the classification of activities from different users. If ADA detects no activity, it implies no classification phase is needed and Wi-Chase considers it as a static environment without the presence of human activities.

IV. Methodology

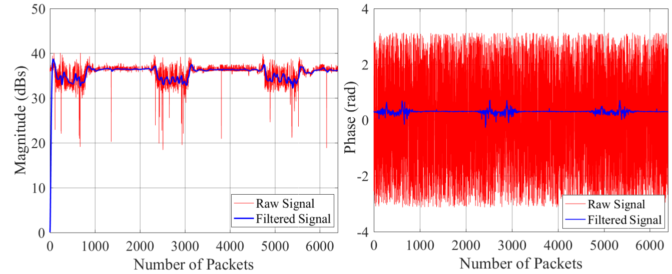
In this section, we detail the design of Wi-Chase. As introduced in the previous section, the first step of Wi-Chase is the sensing and collection of CSI for all T_x-R_x antenna pairs. We then process these collected data for profile construction of different activities. The proposed system architecture and an efficient ADA algorithm enable Wi-Chase to detect any fine-grain human activity. We note that unlike Wi-Sleep [11], the detailed subcarrier level system design with integrated amplitude and phase features efficiently detects and classifies each human activity with high accuracy. It involves five steps as described below.

A. CSI Data Selection

Wi-Chase analyzes multiple subcarriers and links to select the best (with high variance) for the activity recognition. Therefore, in Wi-Chase we only utilize the least noisy communication links but utilize all the subcarriers to filter high frequency and MCS noise using low pass filter as described in next step.

B. Low Pass and MCS Index Filtering

Human activities in general consist of low frequency components in the spectrum whereas noise usually comprises of high frequency contents. In order to eliminate high frequency noise, we incorporate a second order low pass Butterworth filter in the design that has relatively flat magnitude response and keeps phase information intact without introducing distortion.



(a) Magnitude. (b) Phase.

Fig. 3. Raw and filtered CSI of 1^{st} subcarrier.

Through experiments, we determine that human activities of interests in this paper (including walking and running) generally have a maximum frequency around 1 Hz. To effectively detect these low frequency activities, we set the packet sampling rate at F_s = 80 packets/s, same as a normalized cut-off frequency $w_n = 2\pi f/F_s = 0.025\pi$ rad/s. Fig. 3 shows the raw and filtered magnitude and phase of 1^{st} subcarrier (only one subcarrier is shown for clarity). The figure clearly demonstrates that Butterworth filter successfully removes most of the high frequency noisy components from the CSI subcarrier and keeps low frequency activity based perturbations intact.

C. Activity Detection Algorithm (ADA)

To analyze filtered data for activity detection, we design ADA algorithm that exploits variance amongst the subcarriers resulted from multipath reflections. We observe that different human activities around the experimental settings cause unique perturbations in the CSI as shown in Fig. 3. However, different subcarriers show correlated variations for any activity as shown in Fig. 4 (only 10 subcarriers shown in different colors with vertical offsets for clarity).

Different from existing works, we use correlated variations in all these subcarriers and perform majority voting among subcarriers to accurately classify an activity. Through experiments, we observe that the variance among different subcarriers varies remarkably in case of any human activity and remains stable for no activity. This is clearly shown in Fig. 4, where there are three activities and two stationary intervals between them. As a result, anomalies can be extracted by taking advantage of the variance.

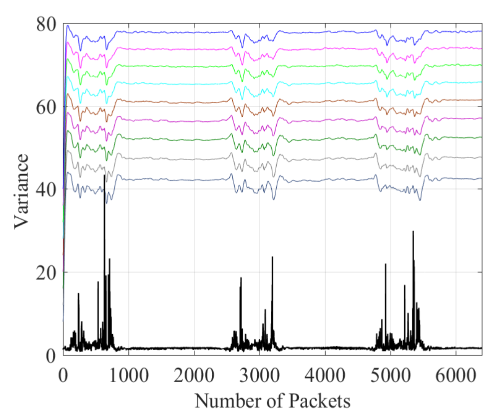


Fig. 4. Variance among subcarriers of a single communication link.

Let ν_i represents variance among the subcarriers of a single link for a packet index i. For N received packets $\boldsymbol{\nu} = \{\nu_i, \nu_{i+1}, \cdots, \nu_N\}$, we assume that it follows Gaussian distribution such that $\boldsymbol{\nu} \sim N(\mu, \sigma^2)$. We first normalize ν_i using Eq. (5) so that $\mathbf{Y}$ follows standard normal distribution such that $\mathbf{Y} \sim N(0, 1)$.

$$Y_i = \frac{(\nu_i - \mu_i)}{\sigma_i} \tag{5}$$

We then define activity indicator threshold $\sigma_{th} = \lambda * \text{std}(\mathbf{Y})$ based on the standard deviation of all the subcarriers for comparison with normalized Y_i (where $\lambda = 1.5$ is empirically determined). The threshold can be determined by preliminary measurements for different scenarios and environments. If the normalized variance Y_i is greater than σ_{th} then Wi-Chase detects it as an activity and Z_i is set to 1 and 0 otherwise. Mathematically, we can describe it as

$$Z_i = \begin{cases} 1, & Y_i \geq \sigma_{th} \\ 0, & Y_i < \sigma_{th} \end{cases}. \tag{6}$$

In few instances, we observe that there are some outliers in static segment of CSI because of noise and other external factors. In order to avoid false anomaly detection thereby, Wi-Chase adheres second level filtering. Let $\mathbf{S_i}$ be a vector representing the accumulation of Z_i between $i - \epsilon$ and $i + \epsilon$ where ϵ is a small interval around packet with index i. S_i can be represented as

$$S_i = \sum_{i-\epsilon}^{i+\epsilon} Z_i. \tag{7}$$

If S_i is a value smaller than empirically determined threshold η_{th}, then Wi-Chase considers it as a false anomaly due to noises. We assume that any activity will last at least for 1 second and use $\eta_{th} = 5$ and $\epsilon = 1$ second in our experiments. By analyzing CSI packets stream this way, ADA can correctly determine the anomalies with an average accuracy of more than 97%.

D. Data Extraction for Human Activity

The ADA algorithm in our design segments CSI into activity and non-activity (static) partitions. For data extraction, Wi-Chase works on the filtered CSI obtained from the Butterworth filter along with the onset of activities provided by ADA. We represent the number of subcarriers between a single link of $N_T \times N_R$ as S_b. Using these, we extract CSI values of N_a successive data packets for any human activity. We represent the CSI of first data packet identified by ADA in the previous step as $\mathbf{H_a(s)}$, where $\mathbf{H_a(s)}$ is $S_b \times 1$ dimensional vector having the CSI values of all the subcarriers.

E. Features Extraction and Training

After data extraction, Wi-Chase possesses precise information of the onset of activities and CSI corresponding to these activities. The next critical step is to precisely classify the type of activity being performed by the human subject. For this purpose, we define integrated features using both magnitude and phase that characterize each of these activities efficiently in contrast to only magnitude or phase features. Through experiments and analyzing extracted CSI, we define six characteristic features for both magnitude and phase to classify different human activities.

1) Mean: One feature is mean $m(k)$ that is simply the average CSI of all the packets H_a for the k^{th} subcarrier of the activity detection segment. Mathematically it can be expressed as

$$m(k) = \frac{[H_{ak}(s) + H_{ak}(s+1) + \cdots + H_{ak}(s+N_a)]}{N_a} \quad \forall k \in [1, S_b]. \tag{8}$$

2) Standard deviation: The second feature is the standard deviation $\sigma(k)$ among the anomalous packets of the k^{th} subcarrier. This serve as an important feature to distinguish between different types of human activities. It can be described mathematically as

$$\sigma(k) = \sqrt{\frac{\sum_{i=s}^{i=s+N_a} (H_{ak}(i) - m(k))^2}{N_a}} \ \forall k \in [1, S_b]. \tag{9}$$

3) Percentiles: The third and fourth features in Wi-Chase is the 25$^{\text{th}}$ percentile $p_{25}(k)$ and 75$^{\text{th}}$ percentile $p_{75}(k)$ for the k^{th} subcarrier. The P-th percentile of an ordered N_a CSI sorted values is the smallest value in the CSI vector such that P percent of the CSI is less than or equal to p-th value. It is obtained by finding the ordinal rank and the corresponding CSI value of that rank for the k^{th} subcarrier. Mathematically, it can be expressed as following.

$$p_{25}(k) = H_{ak}(\lceil \frac{25}{100} \times N_a \rceil) \quad \forall k \in [1, S_b], \tag{10}$$

$$p_{75}(k) = H_{ak}(\lceil \frac{75}{100} \times N_a \rceil) \quad \forall k \in [1, S_b]. \tag{11}$$

4) Median absolute deviation: The fifth feature in Wi-Chase is median absolute deviation $MAD(k)$ that measures the variability in CSI for the human activity segment. Mathematically, let $m_e(x)$ represents median of x. We can formulate MAD as

$$MAD(k) = m_e(|H_{ak}(i) - m_e(H_{ak})|) \ \ \forall i \in [1, N_a] \quad \forall k \in [1, S_b]. \tag{12}$$

5) Maximum value: The last feature is the maximum value $m_x(k)$ of the CSI extracted for the k^{th} subcarrier. We can write it mathematically as

$$m_x(k) = max([H_{ak}(s)|H_{ak}(s+1)| \cdots |H_{ak}(s+N_a)]) \quad \forall k \in [1, S_b]. \tag{13}$$

As mentioned earlier, ADA algorithm senses several human motions as an anomalous activity. These activities seems identical as they showed marked deviation in the CSI in comparison to no activity environment. However, for an efficient recognition system these CSI anomalous patterns needs to be further classified into an accurate human activity or combination of activities to generate an automated response accordingly. To distinguish between multiple activities Wi-Chase constructs integrated (magnitude and phase) features based tuple F for each human activity that can be represented as

$$F = \{f_1, f_2, \cdots, f_n\} \subset \xi. \tag{14}$$

Here f_i represent a particular feature and ξ is the features based dataset for all the human activities included in Wi-Chase system. We use two variants of k-Nearest Neighbor (kNN) and Support

Vector Machine (SVM) machine learning algorithms for the classification of human activities. We test Wi-Chase accuracy with fine kNN that uses one neighbor and weighted kNN that uses ten neighbors.

We get decision from each classifier and consider all the subcarriers from a received packet to label a test activity. Majority voting at the subcarrier level is then performed to assign a final label to the test activity. In particular, if $q(x)$ represents a decision for a particular estimation point x then decision vector for all subcarriers is $\mathbf{q} = [q(1), q(2), \cdots, q(30)]$, and the final predicted label for any packet by Wi-Chase will be

$$L = \max_{j \in [1,2,\cdots,n]} \left[\frac{\sum_{i=1}^{30}(q(i) == j)}{30}\right]. \tag{15}$$

V. Implementation and Evaluation

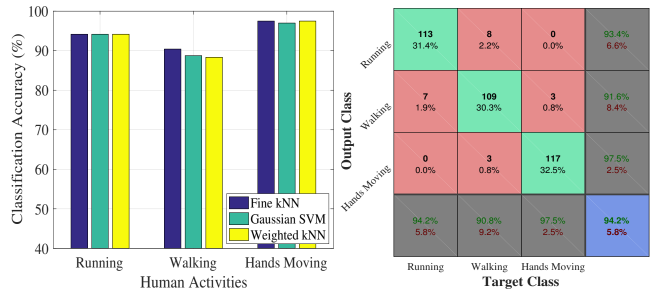
In this section, we perform experimental studies to evaluate the proposed Wi-Chase system. We have used commercially available WiFi devices. In particular, we use a stationary laptop (Sony Vgn series) with an Intel WiFi NIC 5300 network adapter. This serves as the receiver (RP) in our system, capturing channel state information. A Linksys EA4500 Dual Band router acts as the transmitting AP. This AP is configured to work in IEEE 802.11n AP mode at 2.4 GHz frequency and uses three built in antennas. This provides us an access to 3x3 MIMO system with large spatial diversity. The software used to capture and extract CSI data includes Linux Ubuntu 12.04 LTS operating system with a modified kernel [18] and wireless driver for Intel 5300 NIC. This setup enables us to collect ICMP packets with $S_b = 30$ subcarriers for all T_x-R_x antenna pairs. We use MATLAB R2016a to perform data processing and human activity detection.

A. Data Collection

For performance evaluation of Wi-Chase system, we collect CSI when 12 students perform activities in lab settings (6 $\times$ 8 meters). These university students volunteered for the data collection and have no technical knowledge of Wi-Chase system. We collected 720 samples (12 students$\times$20 samples$\times$3 activities) of activities from these students to construct the training and testing dataset. We set a static activity interval (10-20 seconds) between every activity performed so that Wi-Chase can differentiate between multiple activities rather then considering different activities as a single continuous activity.

B. Performance Evaluation

We perform multiple experiments with varying parameters to evaluate our system performance. From our dataset of 720 samples, we initially use 360 samples (12 students$\times$10 samples$\times$3 activities) to train the classifier and remaining 360 samples to test the accuracy of the system. We analyze the accuracy with no cross-validation to avoid any protection against over fitting. However, to validate the proposed contributions and test the dependability on different factors, we perform several experiments and observe the effect on the average classification accuracy. We present and discuss the results for each of these experiments below.

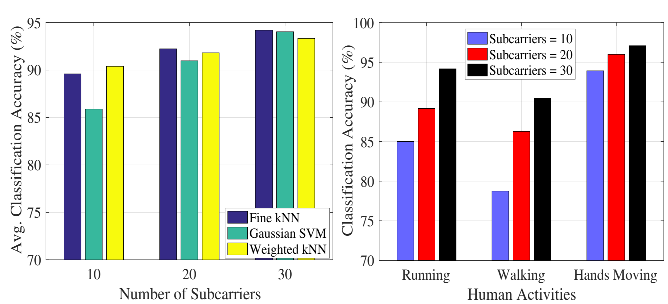


(a) Accuracy of different activities. (b) Confusion matrix of Fine kNN.

Fig. 5. Classification accuracy and confusion matrix.

*1) **System Accuracy with equal samples from all users:*** We first evaluate Wi-Chase system when CSI dataset is split equally for training and testing purposes. In our first experiment, we use 10 samples of each activity from every user to train kNN and SVM classifiers. This gives a training dataset of size 10800×13 as we use 12 features (magnitude and phase) and a class label for all the 30 subcarriers of 12 subjects. We use a majority vote of 30 subcarriers for a received packet to decide about the activity performed. The classification accuracy (percentage) of Wi-Chase system for each of the activity performed by the subjects as classified by different classifiers is shown in Fig 5a. It becomes evident that our system classifies all the three activities with high accuracy unlike other systems like Wi-Sleep [11] that use only few subcarriers. The accuracy of "Hand Moving" is highest because of similar repeating patterns in contrast to walking and running activities. We obtain an average accuracy of 94.2%, 89.2% and 97.3% for running, walking and hands moving activity as shown in Fig 5a. We also plot the confusion matrix for best performing Fine kNN classifier in Fig. 5b to give detailed classification accuracies. This result indicates that different activities could be detected with an average accuracy of 94.2% with Fine kNN classifier.

*2) **System Accuracy with varying number of subcarriers:*** We observe that each of the subcarrier for any particular link undergoes a correlated variation because of reflections caused by any human activity as shown in Fig. 4 previously. Many existing works like [11], use either one or a small subset of subcarriers to design their systems. This limits the system to detect only coarse level activities with low accuracy. Instead, we have proposed that each subcarrier carries integral information that will improve the recognition accuracy because of detailed correlated information content in different subcarriers. To verify



(a) Accuracy of different classifiers. (b) Accuracy of human activities.

Fig. 6. Classification accuracy with varying subcarriers.

this hypothesis, we analyze the classification accuracy of Wi-Chase system as we vary the number of subcarriers from 10 to 30. The plot of average classification accuracy of all the activities for different number of subcarriers is shown in Fig. 6a. We observe that as we increase number of subcarriers, the classification accuracy improves significantly but only at the cost of increased complexity and storage of larger training dataset. Increased number of subcarriers contains extra information and benefiting detection of fine features that are hard to detect using subset of subcarriers. The classification accuracy of each activity as we vary the number of subcarriers from 10 to 30 for Gaussian SVM classifier is shown in Fig. 6b. We can see that classification accuracy of running, walking and hands moving improves by 10.79%, 14.82% and 3.38% as we increase the number of subcarriers from 10 to 30.

*3) **System Accuracy with multiple T_x-R_x Links**:* We use MIMO antennas based router as an AP for data collection. In our experiment, there are 3 transmitting antennas and 3 receiving antennas, resulting in 3×3 MIMO links. Each of these links undergo different attenuation and reflections because of physically displaced placement of antennas on both transmitter AP and receiver laptop (RP). We anticipated that each link carries integral information about human activities and propose integration of information from multiple links to improve classification accuracy. Table I summarizes the effect of multiple links on the classification accuracy for Fine kNN and Gaussian SVM classifiers. The proposed integration improved average accuracy of our system from 94% to 97%. This is because data aggregation from multiple links helps construct and classify the activity even if a single link fails to capture all the CSI perturbations due to an activity.

TALBE I. PERCENTAGE CLASSIFICATION FOR DIFFERENT T_X-R_X LINKS

L/A	1 Link		2 Links		4 Links		6 Links	
	kNN	SVM	kNN	SVM	kNN	SVM	kNN	SVM
R	94.2	94.2	99.2	99.2	98.3	98.7	97.5	98.3
W	90.8	88.8	88.3	88.3	91.7	90.2	92.5	93.3
HM	97.5	97.1	99.6	99.1	99.6	100	99.6	100
Avg.	94.2	94.0	95.7	95.6	96.5	96.3	96.5	97.2

L/A: Links/Activities, kNN: Fine kNN, SVM: Gaussian SVM, R: Running, W: Walking, HM: Hands Moving

VI. Conclusions and Future Work

In this paper we have presented Wi-Chase, a sensorless system, to track human presence and activities using CSI of WiFi signals. Wi-Chase is an efficient recognition system that detects human activities using channel variations caused by multipath fading and reflections. We employ signal processing techniques to process and analyze CSI at subcarrier level. The processed information is used to define and extract characteristic activities based features. The features are trained using machine learning algorithms like kNN and SVM to construct training dataset for the activities. Different from existing works, we exploit subcarrier level majority voting along with integrated features to classify activities of different users. The results obtained validate that our system can achieve an average accuracy greater than other similar systems. We have also presented the optimal values of various system parameters like number of subcarriers and communication links to achieve desired accuracy. We show that multiple links improves Wi-Chase accuracy to 97%. In future, we plan to analyze CSI involving multiple users performing distinct activities and expect to decouple these activities and modify Wi-Chase to do gestures recognition for each user.

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