A Novel Benchmark on Human Activity Recognition Using WiFi Signals

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***Abstract*—WiFi-based Human activity recognition has attracted attention in the human-computer interaction, smart homes, and security monitoring fields. We first construct a WiFi-based activity dataset, namely WiAR, to provide a benchmark for existing works. Then, we leverage the moving variance of CSI to detect the start and end of activity. Moreover, we present K-means-based subcarrier selection mechanism according to subcarrier's sensitivity on human activity to enhance the robustness of human activity recognition. Finally, we leverage several classification algorithms to evaluate the performance of WiAR. Our results show that WiAR satisfies primary demand and achieves an average accuracy of greater than 93% using SVM, 80% using kNN, Random forest, and Decision tree.**

I. Introduction

Human activity recognition is a key component that enables a wide variety of applications such as smart-homes, health care, tracking and building surveillance. In terms of system components, there are three approaches have been proposed to recognize activity: camera-based [1]–[3], sensor-based [4]–[7], and Radio-based [8]–[13]. Cameras can provide high resolution data for activity recognition but privacy is a serious concern. Moreover, weak light and Non-Line-Of-Sight also impede the development of camera-based activity recognition. Although there is no privacy concern with the sensor-based approach, it is inconvenient sometimes because of the sensors that users have to wear. Fortunately, WiFi-based human behavior recognition systems such as activity-based [10] [14] [15], gesture-based [16], and keystroke-based [17], have been proposed to overcome the above limitations in recent years.

WiFi-based activity recognition works have achieved excellent results on the accuracy of activity recognition yet are not easy to be verified due to inherent characteristics of WiFi signals. Therefore, we attempt to construct a WiFi-based activity dataset using commodity wireless devices as a public benchmark to evaluate and compare the above-mentioned WiFi-based works as well as camera-based activity dataset [18] [19]. Meanwhile, we face several data quality, standard activity, dataset's scale, assessment criteria, and signal processing issues in WiAR dataset we construct. For example, collecting data with noisy, activity diversity operated by different users, and these key issues enhance the difficulty of our work. Therefore, we propose a WiFi-based activity recognition framework shown in Figure 1. It consists of three modules such as preprocessing, feature detection and selection, and activity recognition.

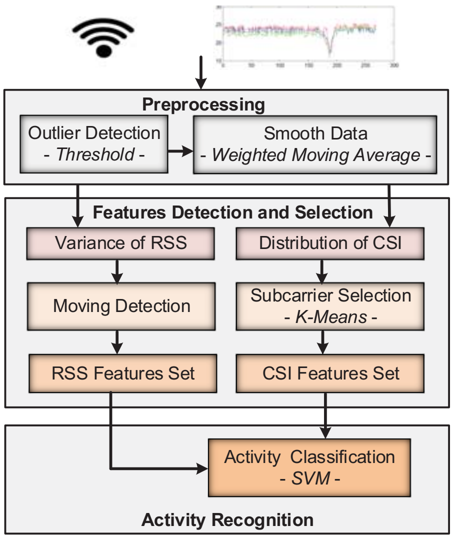

Fig. 1. Framework of Activity Recognition Using WiFi Signals

To summarize, the contributions of this paper are shown as follows:

- We first construct a WiAR, WiFi-based activity dataset, as a benchmark to evaluate the performance of existing activity recognition systems. We use kNN, Random forest, and Decision tree algorithms to verify the effectiveness of the WiAR dataset.
- We leverage several signals processing methods to obtain the high-quality dataset. Then, We analyse RSS characteristics to evaluate the relationship between RSS fluctuation and moving human, and detect the start and end of activity using the moving variance of CSI.
- We design K-means-based subcarrier selection mechanism according to subcarrier's sensitivity to improve the robustness of activity recognition.

The rest of the paper is organised as follows. Section II presents related work. Section III introduces the preliminaries and WiFi-based activity dataset WiAR. We present K-means-

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based subcarrier selection mechanism in Section IV. Then, we analyse the experiment results in Section V. Finally, the conclusion of our work is shown in the Section VI.

II. Related Work

Early works [20]–[22] explore the attenuation characteristics of WiFi signals to locate the human's location and count the number of human in the indoor environment. Then, researchers study WiFi signals reflected by human body to sense human behavior [8] [23]–[25] using coarse-grained information RSS. For example, WiGest [26] studies the relationship between RSS fluctuation and simple gestures to control media player application actions such as turn off, turn on, and fast forward, and achieves accuracy of 96% without training. We attempt to explore RSS change reflected by complex activity and evaluate the relationship between RSS fluctuation and moving behavior.

Due to the limitation of RSS, an increasing number of researchers begin to explore fine-grained channel state information (CSI) to sense human behavior. CSI can captures the tiny behavior [9] [10] [15] [27] [28] in terms of activity location, speed, and direction. WiFall system [9] detects a fall behavior by learning the specific CSI pattern. E-eyes [10] recognizes walking activity and in-place activity by comparing them against signal profiles. Walking activity causes significant pattern changes of the CSI amplitude over time, since it involves significant body movements and location changes. In-place activity only involves relative smaller body movements and will not cause significant amplitude changes with repetitive patterns. Moreover, CARM [14] shows the correlation between CSI value dynamics and human activities by constructing CSI-speed and CSI-activity model. WiDance [29] achieves motion direction using the doppler shifts for the Exergames. With the inspiration of the above mentioned works, we propose a framework of WiFi-based activity recognition to improve the human activity robustness using a WiAR dataset.

III. Preliminaries

A. RSS and CSI

***R**eceived **S**ignal **S**trength* (RSS) in the level of packet represents signal-to-interference-plus-noise ratio (SINR) over the channel bandwidth. Equation (1) gives the definition of RSS as follows.

$$RSS = 10\lg\left(\|V\|^2\right) \quad (1)$$

V is signal voltage, and RSS is the receive signal strength (received power) in decibels (dB). RSS is also mapped into the distance according to Log-normal distance loss model to roughly locate users or devices.

***C**hannel **S**tate **I**nformation* (CSI) contains amplitude and phase measurements separately, and it depicts multi-path propagation at the granularity of OFDM subcarrier in the frequency domain. Each CSI depicts the amplitude and phase of a subcarrier as follow.

$$h_i = |h_i|\, e^{j\sin\theta_i}, \quad i = 1, 2, ..., 30 \quad (2)$$

where h_i is CSI value of the ith subcarrier, $|h_i|$ and θ_i are the amplitude and phase respectively. We study the characteristics of CSI to sense activity in the following sections.

B. Analysis of Body Movement

To preferably study WiFi signals reflected by human activity, we analyse the evolution process of each activity operated by human. We study skeleton joints collected by Kinect to learning the character of activity. From the view of skeleton joints, an activity is divided into two parts including up-body and down-body. Up-body contains five joints (right elbow, left elbow, right hand, left hand, and head) and two benchmark joints (neck, torso) without directions. Down-body contains four joints (right foot, left foot, right knee, left knee). We implement the tracking of skeleton joints and plot activity trajectories using QT tool. We observe that the adjacent joints of high arm wave behavior keep the similar track shown in Figure 2, and some joints of the whole body slightly move influenced by local activity. According to the physical characteristic of each activity, we explore human activity recognition using WiFi signals.

Fig. 2. High Arm Wave Tracking Using Skeleton Data. The activity has two active joints (right hand, right elbow), and the direction changes with every new moving clockwise. However, other joints also keep stability with limits.

C. Constructing WiFi-based Activity Data Set

Due to the sensitivity of WiFi signals, human activity recognition systems are hard to re-completed and evaluated by peer researchers. Moreover, there is no WiFi-based public activity dataset as well as video-based activity dataset at present. Therefore, we construct a WiAR dataset which collects RSS and CSI in three indoor environments such as empty room, meeting room, and office. Table I lists 16 activities and three environments. Each activity is performed 50 times by 10 volunteers in the three indoor environments. We only use a single AP with Intel 5300 card. Volunteers include five females and five males, and the height ranges from $150cm$ to $185cm$.

According to room and furniture layout, the environment complexity is divided into three levels such as empty environment, normal environment, and complex environment. First, empty environment describes no people and furniture around it. We can obtain the high-quality WiFi signals from empty room, and treat it as a ground truth. Then, normal environment contains furniture and no moving people. Compare to the empty environment, multi-path effect from the furniture enriches information diversity reflected by human activity . Finally, there are furniture and moving people in the indoor environment, namely complexity environment. The

TABLE I
WIFI-BASED ACTIVITY RECOGNITION DATASET (WIAR)

Granularity	Activities	Environments	Devices
Activity	Forward kick, Side kick, Bend, Walk, Phone call, Sit down, Squat, Drink water.	Empty room, Meeting room, Office	Router, Laptop with 5300 card
Gestures	Horizontal arm wave, Two hand wave, High throw, Toss paper, Draw tick, Draw x, Cell phone, High arm wave	Empty room, Meeting room, Office	Router, Laptop with 5300 card

performance of WiAR dataset is shown in the following section V.

IV. HUMAN ACTIVITY RECOGNITION USING WIFI SIGNALS

A. Pre-processing

Existing noises in the collecting data increase the difficulty of activity recognition due to the tiny differ between noise and WiFi signals reflected by a fine-grained activity. We attempt to detect existing outliers using variance-based method, and then remove high frequency signals using low-pass filter. Finally we reduce sawtooth wave using weighted moving average.

1) Outlier Detection and Removing High Frequency: Outlier value has an important impact on the data quality because outlier value increases or decreases the fluctuation of WiFi signals. We analyse the distribution of RSS values to evaluate the possible experience-threshold, and combine with variance of RSS to roughly detect outlier point. After detecting outlier, activity causes low frequency change of CSI according to we observe waveform of CSI reflected by activity. Therefore, we adopt low-pass filter to remove high frequency signals.

2) Weighted Moving Average: After removing the galling of signals and alleviating the sharp change of signals, we smooth the CSI data by using weighted moving average as WiFall [30]. CSI is sensitive to room settings or moving human, and the received fluctuation of CSI caused by indoor environment is hard to distinguish from fluctuation caused by an activity. $CSI_{t,1}$ is CSI value of the first subcarrier at time t. $\{CSI_{1,1}, ..., CSI_{t,1}\}$ indicates the CSI value sequence of first subcarrier in the time period t. The CSI value at time t is averaged by the previous m values. The latest CSI has weight m, the second latest $m-1$, and so on. The expression of CSI series is shown as follows.

$$CSI_{t,1} = \frac{1}{m + (m-1) + \cdots + 1} \times (m \times CSI_{t,1} + (m-1) \times CSI_{t-1,1} + \cdots + 1 \times CSI_{t-m-1,1}) \tag{3}$$

where $CSI_{t,1}$ is the averaged new CSI. The value of m decides in what degree the current value is related to historical records. In our study, we set m according to the experience method and trail method. We first set m to 5 which the window length is 5 packets. With the m increasing, CSI fluctuation using weighted moving average algorithm becomes smoother. Finally, we set m to 10 to achieve the optimal results because each activity produces a peak in about 10 packet periods.

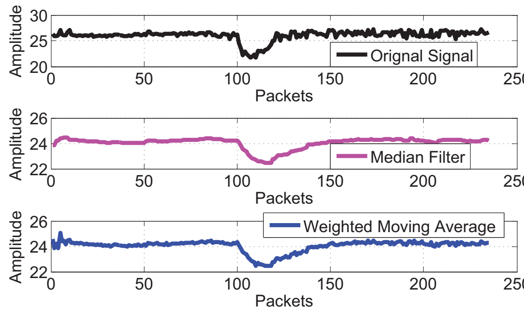

Fig. 3. Comparison of Signal Filtering Methods

B. Features Extraction

Plenty of related works summarize the important of feature selection for human activity recognition in the dynamic indoor environment. We first segment activity before extracting activity features according to activity characteristics.

1) Activity Segmentation: Activity segmentation mainly removes the non-activity sequence packets from collecting data sequence of activity. We propose two methods to detect the start and end of activity and improve the robustness of segmentation algorithm. First, we remove the first second and the last-second data sequence of the activity to reduce the error of true activity sequence in our experimental environment. But, this method is invalid in the practical environment due to the unknown time which each activity costs. Therefore, we propose the second method to solve the above mentioned problem. We leverage moving variance of CSI for activity to detect the start and end of each activity. The sequence of activity data is defined as $X = \{x_1, x_2, ..., x_n\}$. We use the standard deviation instead of variance of CSI as follows.

$$\sigma_i = \sqrt{\frac{\sum_1^m (x_{i+j-1} - \bar{x})^2}{m}}, (i = 1, 2, ..., n-m) \tag{4}$$

where m represents a step-size, and $\bar{x}$ is a mean value of samples.

We construct a window per 10 packets from the packet sequence of each sample, and compute the variance of the window sequence. Then, we construct the moving variance

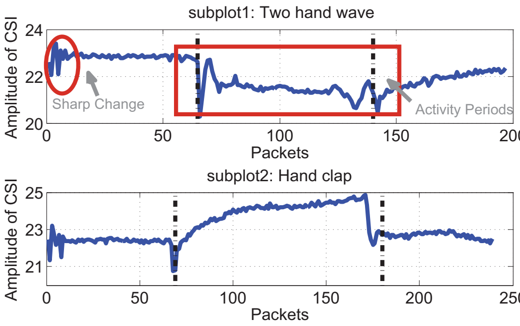

Fig. 4. Segmentation Point of Similar Activity

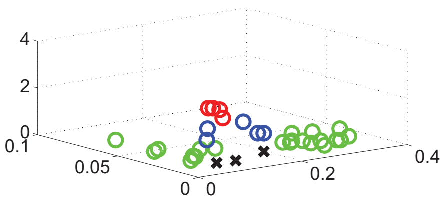

Fig. 5. Clustering Subcarriers

histogram and compare with other strength windows. Finally, we can detect the sharp points of each activity, and roughly recognize the start and end of each activity from the data sequence. Figure 4 shows the start and end of activity periods. Red circle describes sharp change of CSI at the starting point of collecting activity data, and red rectangle represents the duration of activity. Moreover, black dotted line roughly represents the start and end of activity. Detecting the start and end of activity still exists a small error due to signal sensitivity.

2) Subcarrier Selection and Features Detection: According to our observation, subcarriers have similar change trends for the same activity, but they have different sensitivity for different activities. Therefore, we select the obvious subcarriers reflected by activity using K-means algorithm to sense human activity. Figure 5 shows that 30 subcarriers are divided into 3 clusters according to the sensitivity on activity.

RSS describes a coarse-activity in the static environment such as walking, bend, and sit-down. Therefore, we consider the characteristics of RSS to recognize coarse-activity. First, we get the waveform of RSS for each activity by using filtering method, and evaluate the change of RSS using the local variance according to the segmentation activity sequence. Then, we detect and evaluate the location of peak value and the number of peak as the signatures of each activity. Finally, we extract the relationship between RSS peak and activity to recognize the coarse-activity in static environment.

Then, features we extract include variance, envelope of CSI, signal entropy, velocity of signal change, median absolute deviation, period of motion, and normalized standard deviation of CSI from selecting subcarrier. We are interested in a more general representation features for human activity recognition. Finally, we construct the fusion features set of RSS and CSI. In our work, we exploit features set in term of activity itself and signals change reflected by the activity.

C. Activity Recognition

We select a high effective SVM classification to recognise sixteen activities according to the performance of existing works. In the following sections, we also verify that the performance of SVM precedes others. RSS feature set and CSI feature set as input of SVM trains the optimal model to achieve the stable accuracy of activity recognition. The outputs of SVM contain accuracy, predict_label, and prob_estimates. We evaluate the performance of classification algorithm according to the accuracy, and achieve the accuracy of activity recognition using predict_label.

V. Implementation & Evaluation

A. Experimental Setup

We use a commercial TP-Link wireless router as the transmitter operating in IEEE 802.11n AP mode at 2.4GHz. A ThinkPad 400 laptop with three antennae running Ubuntu 10.04 is used as a receiver, which is equipped with off-the-shelf Intel 5300 card and a modified firmware. During the process of receiving WiFi signals, the receiver pings 30 $pkts/s$ from the router and records the RSS and CSI from each packet. Figure 6 lists three experimental environments to explore the impact of indoor environment on the performance of activity recognition. The distance between receiver and transmitter is 6m, and volunteer stands the middle point of transmitter-receiver without obstacles.

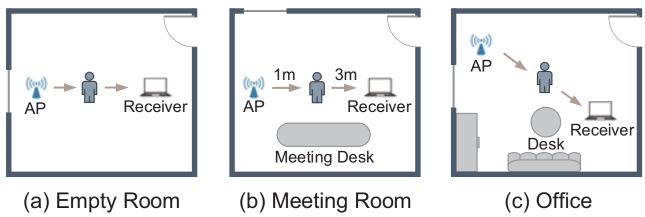

Fig. 6. Experimental Scenarios

B. Evaluation

The section analyses and elaborates the accuracy and influencing factors of activity recognition using CSI in the following four aspects: human diversity, similar activities, different indoor environments and training-sample size. Moreover, we also evaluate the performance of WiAR using four classification algorithms.

Human diversity not only increases the diversity of CSI, but also it raises the difficulty of activity recognition because people have different motion styles such as speed, height, and strength. Figure 7(a) shows that we achieve 93.42% of recognition accuracy using selecting subcarrier for all the volunteers. We select two typical volunteers including volunteer A and volunteer B to verify the impact of human diversity on the accuracy. Volunteer A which rarely exercise in the routine lives

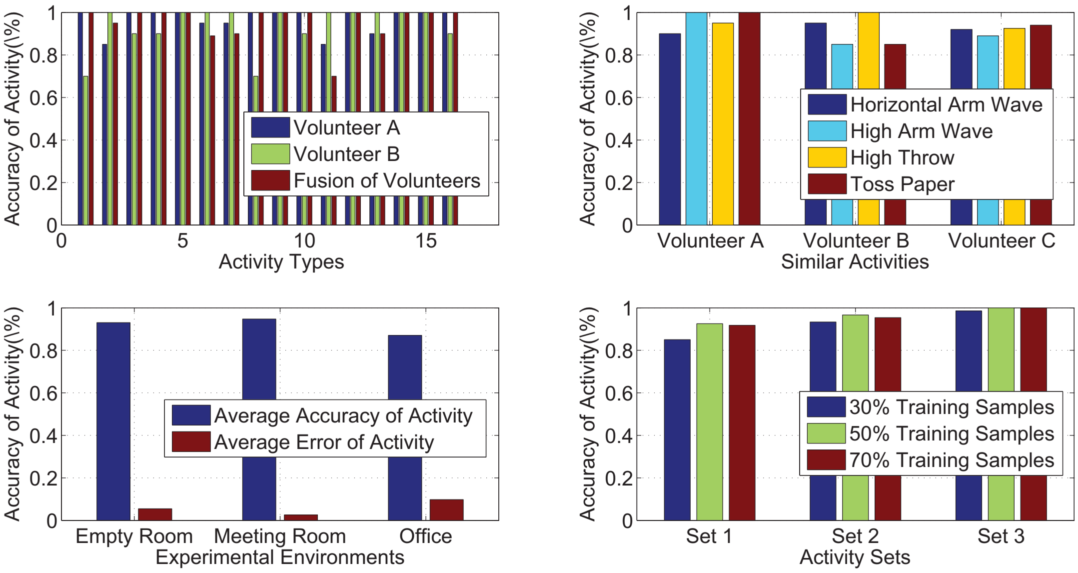

Fig. 7. Performance Analysis of Activities Using CSI. From left to right on the figure sub-figure are, (a) Sixteen activities include horizontal arm wave, high arm wave, two hand wave, high throw, draw x, draw tick, toss paper, forward kick, side kick, bend, hand clap, walk, cell phone, drink water, sit down, squat. (b) Four activities contain horizontal arm wave, high arm wave, high throw, toss paper. (c) The impact of environment on accuracy. (d) The impact of training samples on accuracy of three activity sets.

achieves 93.1% of average recognition accuracy. Volunteer B which often regularly exercise obtains 97.1% of average recognition accuracy. The exercise experience may increase the activity standard, and then improving the recognition accuracy. We randomly select the activity information of three volunteers from the WiAR dataset as fusion information. Through the experiment, this accuracy outperforms the accuracy achieved by using a single volunteer.

Similar activity has a low accuracy of activity recognition. Figure 7(b) describes the recognition accuracy of two groups of similar activity: high arm wave and horizontal arm wave; high throw and toss paper. The first group of activity achieves 92.5% of average recognition accuracy and 94.6% for the second group. The false positive for similar activity is higher than independent activity. For example, forward kick and slide kick are the similar activity, and the difference between them is the moving direction. In order to obtain the better accuracy, we consider the impact of moving direction on the signal. Independent activity keeps the character of itself and produces the unique signal pattern.

We explore the impact of indoor environment on the accuracy of activity recognition using CSI. Figure 6 lists three experimental environments including empty room, meeting room, and office in terms of the complexity. We explore the character of multi-path effect to describe the relationship between CSI change and activity, and extract the signal pattern reflected by the body behavior. Figure 7(c) shows the results about three environments, and the accuracy of meeting room with 94.7% outperforms other two environments, and then 93% for empty room and 87% for office due to the proper paths. The meeting room generates 2.6% of average error, and 9.8% of error in the office due to paths excessively reflected by body. We will deeply explore multi-path effect to improve the robustness and accuracy of activity recognition system using CSI in the future work.

Training-samples size has an important influence on the accuracy of activity recognition using CSI. We design three proof schemes to analyse the influence of different training-samples sizes on the accuracy of activity recognition shown in the Figure 7(d). We first introduce three activity sets and three training-samples sets. Activity Set 1 consists of horizontal arm wave, high arm wave, high throw, and toss paper; Activity Set 2 contains two hands wave and hand clap activity; Activity Set 3 consists of phone, draw tick, draw x, and drink water. Moreover, these activity sets come from the same people. With the size of training-samples increasing, the accuracy of activity recognition is improved by about 11% for Activity Set 1. Activity Set 1 has a low accuracy in the test A because Activity Set 1 contains more similar activities. Although Activity Set 3 also contains similar activities, the accuracy is better than Activity Set 1 due to the strength of activity operated by people.

C. Evaluation of WiAR Dataset

The subsection shows the activity recognition performance using several classification algorithms on the WiAR dataset. We analyse activity data of all volunteers to evaluate the performance of WiAR dataset using kNN with voting, Random forest, and Decision tree algorithms in terms of activity recognition accuracy.

TABLE II
PERFORMANCE COMPARISON BY FOUR CLASSIFICATION ALGORITHMS.

Method	10 Subcarriers			30 Subcarriers		
	A	B	C	A	B	C
kNN	0.875	0.916	0.947	0.916	0.895	0.947
Random Forest	0.885	0.906	0.958	0.906	0.895	0.948
Decision Tree	0.8542	0.822	0.916	0.865	0.834	0.917
SVM	**0.9625**	**0.9688**	**0.975**	**0.94375**	**0.90625**	**0.9375**

We study the impact of subcarrier and antennae on performance of activity recognition by using four classification algorithms shown in Table II. It shows that the accuracy using SVM outperforms other classification algorithms, and 10 subcarriers obtained by subcarrier selection mechanism increase 4.26% accuracy compared to activity recognition using 30 subcarriers. Three antennae such as A, B, and C, increase the diversity of CSI data, and keep more than 80% of activity recognition accuracy.

VI. CONCLUSION

In this paper, we make three contributions as follows. First, we construct a WiAR dataset, WiFi-based activity dataset, as a public dataset to evaluate the performance of existing works. Second, we evaluate the correlation between RSS fluctuation and coarse-activity by exploring RSS characteristics. Third, we design K-means-based subcarrier selection mechanism to improve the robustness of human activity recognition in dynamic environments. Experimental results show that WiAR dataset can satisfy primary demand, and we achieves an average accuracy of greater than 93% using SVM, 80% using kNN, Random forest, and Decision tree. We will increase the diversity of WiAR dataset in terms of activity, location, direction, and speed in the following work.

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