An Experimental Study of Harvesting Channel State Information of WiFi Signals

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***Abstract*—With the pervasive wireless communication networks and devices, WiFi has become an indispensable part of our daily life. The features of WiFi signals are commonly characterized using the received signal strength indication (RSSI) and the channel state information (CSI). In recent years, many machine learning algorithms have been proposed to analyze CSI of WiFi signals for various applications, such as indoor localization and gesture recognition. In this paper, we conduct an experimental study of harvesting channel state information of WiFi signals and evaluate the impact of various factors on the quality of these CSI data. Our measurement results show the randomness and the inefficiency of the collected CSI samples based on data visualization. Our study may stimulate more attention on the repeatability of the networking experiments and call for more open data initiatives to accelerate the applications of machine learning techniques in networking research.**

***Index Terms*—Channel State Information, Intel 5300, Gesture Recognition**

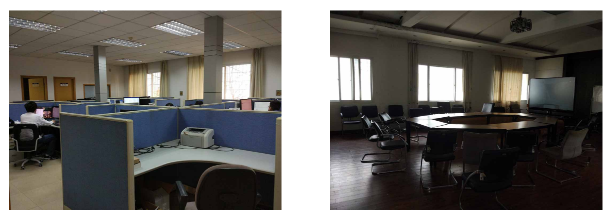
I. Introduction

With the proliferation of mobile wireless devices, WiFi has become one of the dominating network accesses. In addition to the Internet access, many machine learning techniques have been proposed to analyze WiFi signals for various intelligent applications, such as indoor localization and activity recognition because these signals have been inevitably modulated by the wireless environments and generated rich information for the signals from the transmitter to the receiver such as the combined effect of scattering, fading, and power decay with distance. The features of WiFi signals are commonly characterized using the received signal strength indication (RSSI) and the channel state information (CSI).

In [1] and [2], interesting ideas have been proposed to utilize CSI to differentiate human's indoor activities. CSI-based indoor localization techniques require the relationship between CSI data and the distance from the transmitter to the receiver [3], while CSI-based activity recognition techniques require that CSI data contain not only static CSI values but also the changing trend of CSI over time, which bring forth more difficulties in data collection and analysis. The most convenient way to collect CSI is to utilize commercial device, Intel 5300 adaptor with a modified driver [4]. In the paper, we are motivated to examine the repeatability of the CSI experiments for gesture recognition.

II. Method

In this section, we describe the data-collection procedure for the CSI-based activity recognition experiments. We collect the CSI data with ThinkPad T400 with a Intel 5300 WiFi card and two commercially available WiFi access points: NetGear 3700v4 and XiaoMi Router III. The operating system of ThinkPad T400 is Ubuntu 12.04. We conducted our experiments in two places: Room 104 and Room 203 of Internet Technology and Engineering R&D Center of Huazhong University. the former one is a rather complicate lab with people walking around, while the second place is a quiet meeting room with almost no people. The experiment scenarios are shown as Fig.1.



(a) Lab (b) Meeting Room

Fig. 1: Experimental scenes

We use csi-tool [4] to harvest CSI data into the laptop. Our experiments were performed in the 5 GHz frequency band with 20 MHz bandwidth channels. We collect hundreds of samples of four gestures : "Push", "Wave", "Slide" and "Circle", the distances of AP and the laptop is set to 5 m. We conduct our experiments at different times of a number of different days. The diversity of the collected data ensures that our experiments cover different cases.

III. Results

After collecting in total 125 CSI series including hundreds of gestures, we visualize and analyze the data using Matlab R2014a. [1] and [5] proposed machine learning algorithms to pre-process the CSI data and extract the features of each activity. We followed the ideas of above papers but unfortunately, we have experienced difficulties to segment each each activity though we pause a few seconds before another activity [5]. The principal component analysis (PCA) and the discrete Wavelet transform (DWT) do not appear to be successful to extract the features we need and it appears the signals behave very random that different gestures or activities are difficult to be classified.

In [6], CSI variances are leveraged to differentiate different activities. In [5], the third component of PCA and Daubechies D4 wavelet can extract precise features using the Butterworth filter. In this section, we display the visualization of the variances and the features of CSI data series, which exhibit quite strong randomness.

A. Segmentation Variance

Since csi-toolkit uses the Intel WiFi Link 5300 wireless NIC with 3 antennas and each antenna reports CSI for 30 groups of subcarriers, spread evenly among the 56 sub-carriers of a 20 MHz channel or the 114 carriers in a 40 MHz channel [4]. It is shown that the variance of the 30 sub-carriers can serve as good indicators of different gestures [1]. Hence, we are supposed to obtain the start point and the end point of each one gesture through the relative variance.

We conducted experiments on the meeting room and the lab with two different routers, the sampling frequency is set to be 200 Hz in order to get enough bandwidth for transferring actual data [5]. Fig.2 illustrates the amplitude and variance of gesture "wave" in both the lab and the meeting room. It can be illustrated that the normalized variances differ from one to another. The variance in "moving time" is indeed larger yet not obvious; hence, it is difficult to clearly segment different gestures in the lab room. The variances indicator in meeting room obtains much better performance.

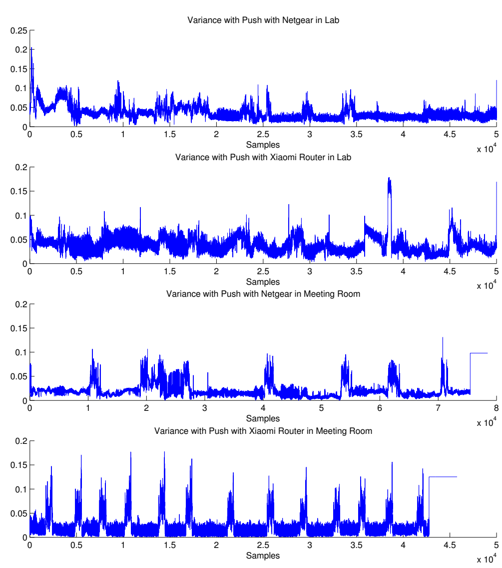


Fig. 2: Normalized variances in different scenes

B. Gesture Features

To avoid the impact of the noise in the signals collected in the lab room, we extract the DWT features of the CSI series using the data collected in the meeting room, with the NetGear Router and the Xiaomi Router. The sampling frequency is also set to 200 Hz. The algorithm follow [5]. Fig. 3 shows four gestures "Push", "Wave" ,"Circle" ,"Slide" with both two routers. We can hardly obtain the feature with eyes. The waves of one gesture collected by one router do not appear to exhibit similar patterns. As a result, we conjecture that the gesture techniques require more in-depth repeated experimentations for previous work.

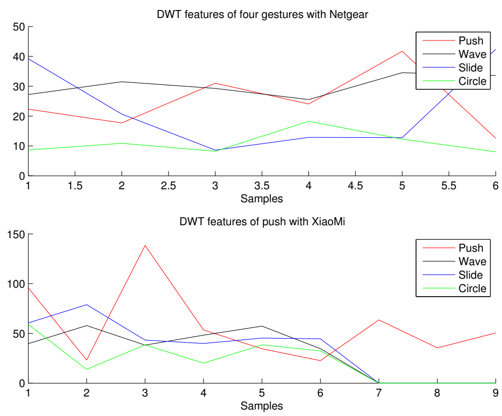


Fig. 3: Averaged DWT features with different routers

IV. Conclusion

In this paper, we repeated typical experiments in previous work trying to recognize different activities or gestures based on CSI as a case study. Our experiment results show that the segmentation is difficult to achieve precisely and notable gesture features are hardly to be extracted in common environments such as the lab room and the meeting room. We reported our experiences in this workshop to stimulate more attention on the repeatability of the networking experiments and call for more open data initiatives to accelerate the applications of machine learning techniques in networking research.

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