Real-Time Human Activity Recognition System Exploiting Ubiquitous Wi-Fi Signals

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***Abstract*—In recent years, the development of wireless network provides the hardware foundation for wireless perception within indoor environment.The wireless sensing system has been applied in many fields, such as intrusion detection, search rescue, gesture recognition and abnormal human activities detection such as falling, wandering behaviour, breathing and heart rates and so on. Among of them, Wi-Fi sensing has proven to be effective since it exploits off-the-shelf low-cost small wireless devices operating at 2.4 GHz frequency band and also a potential field for real-time sensing method for human recognition. This paper presents foundation for real-time Wi-Fi sensing system to detect various human activities when performed in indoor settings.**

***Index Terms*—MIMO, Wi-Fi, Human Activity Recognition, Channel State Information (CSI), RF signals, Machine Learning**

I. Introduction

The Wi-Fi devices based on IEEE 802.11n protocol, have been used widely in household, public service and most of modern constructions as a basic application for user connecting Internet. The popularity of Wi-Fi devices also provides a potential market and user for innovative Wi-Fi perception work. Wi-Fi signal has high sensitivity characteristics to realize the perception ability. It is with this characteristic that we can use the perception ability to passively detect, identify and evaluate human behavior [1] and vital sign [2] [3] .

In physical layer, channel impulse response (CIR) and channel frequency response (CFR) are proposed to feed back the performance of the wireless channel to improve transmission quality, in which CFR is the Fourier Transform of CIR.CSI is the data format used to represent the CFR sampling of subcarrier granularity within the system frequency band obtained from the physical layer by the commercial IEEE802.11n wireless network card based on Orthogonal Frequency Division Multiplexing (OFDM) technology. The basic measuring unit of CSI is a packet, contains time stamp, Received signal strength indicator (RSSI), CSI and etc. Correspondingly, CSI reflect changes of surrounding physical environment. CSI-based Wi-Fi sensing is able to apply characteristics of wireless multi-path propagation, analyzes the state changes of its multiple subcarriers, and deduces actions and behaviors of users in the non-line-of-sight (NLOS) without carrying a sensor.

Nowadays, a lot of work is done on the basis of non-real-time processing.WiFall [4] was proposed to achieve single-person fall detection with high accuracy, using magnitude of CSI value create fingerprint groups and classifying with Machine Learning. Besides,in [2] and [5],researchers applied CSI phase difference on the two antennas for activity recognition, which can perform a reliable classification of falls and other human activities. Experimental results in [5] four indoor scenarios show that the RT drop is always better than the latest method WiFall, with an average increase of 14%.In [6] Pearson correlation is applied to calculate correlation level between CSI matrix from different antennas in real-time test.

II. Methodology

The essence of Wi-Fi perception is to obtain the current environmental information by analyzing and processing the changes in the signal-to-noise ratio of the physical channel in the CSI data packet within a period of time.

A. Feature Extraction

Feature extraction methods contains normalized standard deviation, period of the motion, median absolute deviation (MAD), interquartile range,information entropy, maximum and minimum of CSI. Different kinds of value reflect the feature of signals directly. Therefore, the different features are calculated and listed in feature table for classification task. In this stage Linear Discriminant Analysis (LDA) and Support Vector Machine (SVM) classification methods are applied to train and test dataset, which are both supervised learning methods. In LDA, it will obtain a subspace from original data in which data of the same class will be concentrated and data of different classes will be dispersed. Therefore,

from this perspective, LDA is more suitable for the task of classification. SVM algorithm was originally designed for binary classification problems. When dealing with multiple types of problems, the parameters of multiple classification surfaces can be combined into one optimization problem. By solving the optimization problem, multi-class classification can be realized.

III. Result and Discussion

A. Experimental Setup

Real-time recognition depend on reliable hardware and driver.In experiment section, two Intel 5300 NICs are applied as AP and monitors in our experiments with two PCs.

B. Experimental Methodology

In this experiment, three types of activities are considered, sit down, stand up, static stand. For each of activities, the higher the sampling frequency, the more detailed information is theoretically contained, which will improve the recognition accuracy. However, a sampling rate higher than 200Hz will greatly increase the processing load of the computer and affect the speed of real-time processing.So all dataset was collected with 200Hz. Collected magnitude of CSI value in single subcarrier of each antennas is shown in Figure 1.

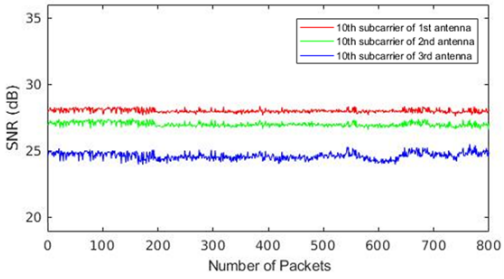

Fig. 1. Real-time plotting of SNR vs number of packets

1) Preprocess: Carrier selection is necessary for real-time sensing. Each CSI data package contains 30 subchannels information with MIMO technology, the data steam can be $[3 * 3 * 30]$ at the maximum. Instead of selecting specific channel, Principal Component Analysis (PCA) and Butterworth Low Pass Filter (LPF) are used to reduce the dimensionality of all subcarries and extract the characteristic from high frequency noise, shown in Figure 2. Next, due to the Human actions in an indoor environment do not have a fixed frequency, and interfere significantly with the amplitude of the physical channel CSI. Based on this property, the system will collect the signal amplitude of CSI and process it to match.

2) Train ML model: There are four types of dataset were collected: none of people, people stand statically, people sit down and stand up respectively. With cross validation, the accuracy of default model for LDA and SVM are 96.4% and 94.6% respectively.

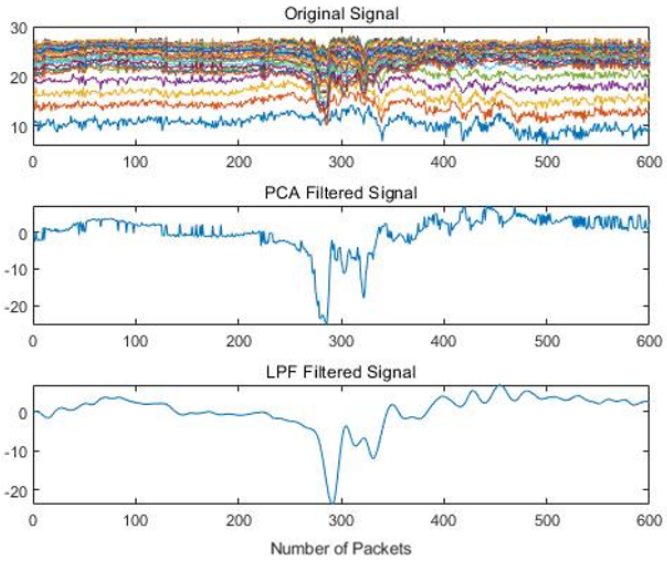

Fig. 2. Processed signal with PCA and LPF

3) Real-time recognition: In [6], code work of real-time reading has been shared online via MATLAB. In test setting, every 5 seconds of receiving the signal, the program classified the collected data with well-trained ML model. In 50 groups test within fixed environment, system has an average delay of 0.3s of data transmission and more than 70% accuracy, proving it availability for further research.

IV. Conclusion

This paper presented real-time human activity recognition system exploiting low-cost wireless devices such as network interface card, Wi-Fi router operating at 2.4 GHz where 30 subcarriers were received by NIC. The results demonstrated that the variances of amplitude information were distincted each time experiment was performed. This system can be used in at homes or hospitals to monitor activities of patients and detect critical events such as falls in elderly people.

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