A Wireless Signal Denoising Model for Human Activity Recognition

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Abstract. Some pioneer WIFI signal based human activity recognition systems have been proposed. The common characteristic is to use the information of CSI(Channel State Information). Experimental results show that the extracted features of the PCA method are more obvious than that of the traditional denoising method. Even in a static environment, CSI values in Wifi signals fluctuate because WiFi devices are susceptible to surrounding electromagnetic noises. General purpose denoising methods, such as low-pass filters or mean filters, do not perform well in removing these impulse and burst noises. In this paper, we propose a method which use the low pass filter and principal component analysis simultaneously. Experimental results show that the extracted features of the PCA method are more obvious than that of the traditional methods.

Introduction

CSI technology based on the human behavior recovery and positioning of the main use of wireless signal, the typical system such as TD-LTE, WIFI physical layer technology. OFDM technology divides the channel into several orthogonal sub-carriers in frequency domain. We can estimate and predict the state of the whole link through the acquisition of the channel information of different sub-carriers. When the receiver is blocked, the signal of multiple sub-carriers will have different effects. If there is a moving object between the transceiver, the change of the action of the object has the characteristics of the consistency of the wireless channel. The amplitude, phase and signal intensity of the wireless signal are mainly affected by the human action. Human activity recognition and wireless location based WIFI signal are the core technology that enables a wide variety of applications such as health care, smart homes, fitness tracking and building surveillance. Traditional approaches based cameras [1] have the fundamental limitations of requiring line of sight with enough lighting and breaching human privacy potentially. Wearable sensors [2] based approaches are inconvenient sometimes because of the sensors that users have to wear. Recently, WIFI signal based human activity recognition and wireless location systems, such as E-eyes [3] and WiHear [4] have been proposed based on the observation that different human activities introduce different multi-path distortions in WIFI signals. So we can make full use of the signal to recognize human activity and location. WIFI NICs continuously monitor variations in the wireless channel using CSI, which characterizes the frequency response of the wireless channel. Let \(x(f,t)\) and \(y(f,t)\) be the frequency domain representations of transmitted and received signals, respectively. The two signals are related by the equation (1), described as follows:

\[
y(f,t) = x(f,t) * h(f,t) + N_i
\]  

(1)

Ni represent an noise vector, where \(h(f,t)\) is the complex valued channel frequency response (CFR) for carrier frequency \(f\) measured at time \(t\). Let \(N_t\) and \(N_r\) represent the number of transmitting and receiving antennas, respectively. As CSI is measured on 30 selected OFDM sub-carriers for a received 802.11 frame, each CSI measurement contains 30 matrices with
dimensions $N_t \times N_r$. Each entry in any matrix is a CFR value between an antenna pair at a certain OFDM sub-carrier frequency at a particular time, we call the time-series of CFR values for a given antenna pair and OFDM sub-carrier as CSI stream. Thus, there are $30 \times N_t \times N_r$ CSI streams in a time-series of CSI values.

**Related Works**

Utilizing wireless signal for human activity recognition and localization can be divided into two categories: Received Signal Strength Indicator (RSSI) based, and CSI based.

**RSSI Based**: RSSI based human activity recognition systems leverage the signal strength changes caused by human activities [5]. This approach can only do coarse grained human activity recognition with low accuracy because the RSSI values provided by the commercial devices have very low resolution. For RSSI based gesture recognition, the accuracy is $56\%$ over 7 different gestures.

**CSI Based**: CSI values are available in many commercial devices such as Intel 5300 and Atheros 9390 network interface cards (NICs). Recently CSI has been used for human activity recognition, as well as indoor localization [6]. Zhou et al. proposed to use CSI to detect the presence of a person in an environment [7]. E-eyes [3] recognizes a set of nine daily human activities using CSI. Note that WiHear [4] and E-eyes use CSI in quite different. WiHear does not effectively denoise CSI values; thus, it has to use directional antennas to reduce the noise in CSI values to achieve acceptable accuracy.

**Signal Denoising Model**

**System Overview**

![System Overview Diagram](image)

The overview of our system is as Fig. 1. Firstly, mean filtering and low pass filtering are performed on CSI original data respectively. The main purpose of these two filters is to remove some of the additive noise and high frequency noise. After filtering is completed, the data is processed by PCA method. According to the extracted features by using Human activity recognition algorithm such as Dynamic Time Wrapping (DTW) or Earth Mover Distance (EMD), the characteristics of the action is determined.

**Noise in CSI Information**

The CSI streams provided by commercial WIFI devices are extremely noisy. One major sources of noise in CSI streams are the internal state transitions in sender and receiver WIFI NICs such as transmission power changes, transmission rate adaptation, and internal CSI reference level changes. These internal state transitions result in high amplitude impulse and burst noises in CSI streams. An interesting feature of these impulse and burst noises is that their effect is highly correlated across all CSI streams, i.e., they affect samples in all streams at the same time. For example, if sender WIFI NIC increases the transmission power by $0.5\text{dB}$, all streams see a power increase of $0.5\text{dB}$. So we don't care the impact of internal noise.
Mean Filter

Mean filter is a typical image processing algorithm, which can effectively filter the additive noise in the image. To denoise the additive noise of CSI streams, we can use this algorithm, take the amplitude of CSI stream as the pixel, then select appropriate size of template. Fig. 2(a) shows the amplitudes of one sub-carry that the unfiltered CSI waveform of Squatting down and standing up, Fig. 2(b) shows the resultant from the mean filter, and The size of mean filter N equal 9. By utilizing the method of mean filter, the waveform becomes smoothly. But mean filter has inherent defects. It removes most of the noise, whereas details of the information are also removed.

Low-pass Filter

(a) Original CSI time series

(b) CSI time series by mean filter
The frequency of variations caused due to the movements of human lies at the low end of the spectrum while the frequency of the noise lies at the high end of the spectrum. To remove noise in such a situation, butterworth low-pass filter is a natural choice which does not significantly distort the phase information in the signal and has a maximally flat amplitude response in the pass band and thus does not distort human movement signal much. Fig. 2(c) shows the result from the Butterworth low-pass filter. Although this process helps in removing some high frequency noise, the noise is not completely eliminated because Butterworth filter has slightly slow fall off gain in the stop band. A simple low pass filter does not perform efficiently. Although strict low-pass filtering can remove noise further, it causes loss of useful information from the signal as well. To extract useful signal from the noisy CSI time series, we observe that the variations in the CSI time series of all sub-carriers due to the movements of human are correlated. Therefore, it applies Principal Component Analysis (PCA) on the filtered sub-carriers to extract the signals that only contain variations caused by movements of human activity.

**Principal Component Analysis**

Principal component analysis (PCA), dimension reduction ideas to use to index into a few more comprehensive index (the principal components), most of the information of each principal component can reflect the original variables, and the information contained in each repeat, This approach in the introduction of various variables and the complexity of the main components, The PCA method has been mentioned in many papers, such as Keystroke Recognition Using WIFI Signals [8] and Understanding and Modeling of WiFi Signal Based Human Activity Recognition [9]. Fig. 3 plots the amplitudes of CSI time series of 4 different sub-carriers. From these figures, we can see that all sub-carriers show correlated variations in their time series. The sub-carriers that are closely spaced in frequency show identical variations whereas the sub-carriers that farther away in frequency show non-identical changes. Despite non-identical changes, a strong correlation still exists even across the sub-carriers that are far apart in frequency. Human activity recognition system leverages this correlation and calculates the principal components from all CSI time series. It then chooses those principal components that represent the most common variations among all CSI time series.
(a) CSI time series of sub-carriers 1st

(b) CSI time series of sub-carriers 5th

(c) CSI time series of sub-carriers 10th
Let $H_{1:p}$ be an $\mathcal{S}\mathcal{C}^p$ dimensional matrix that contains the top $p$ principal components obtained from PCA on $Z_t$ that the original CSI stream matrix be normalized. We remove the first component from those top $p$ principal components based on our observation that the first component captures majority of the noise, while subsequent components contain information about movements or position. Due to correlated nature of variations in multiple CSI time series, the removal of this PCA component does not lead to any significant information loss as remaining PCA components still contain enough information required for successfully human activity recognition and location. And $H_{1:p}$ can be calculated as this expression: $H_{1:p}=Z_tP1_{1:p1}$ on behalf of our calculated transformation matrix selected the first principal component. And so on $H_{2:p}$ calculated by $P2$ include First second principal components. We choose the $P = 4$ in our implementation based on our observation that only top 4 principal components contained most significant variations in CSI values caused by different motions. Fig. 4(d): PCA of normalized CSI stream $Z_t$ is characteristics of the final extraction by PCA and we observed that the most noisy projection among the all 4 projections of $Z_t$ essentially removed.
Implementation and Evaluation

PCA reduces the dimension of the CSI information obtained from the 30 sub-carriers in each Nt*Nr stream, which is useful because using information from all sub-carriers for location and recognition significantly increases the computational complexity of the system. PCA automatically enables CSI stream to obtain the signals that are representative of human activity or position. And PCA helps in removing noise from the signals by taking advantage of correlated variations in CSI time series of different sub-carriers. It removes the uncorrelated noisy components. This PCA based noise reduction is one of the major reasons behind high location and recognition accuracy of our scheme.

In this section, we compare the CSI data collected in the indoor environments. In Fig. 5 and Fig. 6, CSI time series of three types of different human activities are proposed. From the experiment of Fig. 5(b), Fig. 5(c), Fig. 6(b) and Fig. 6(c), the CSI original series is handled by mean filter and low-pass filter, and the noise reduced effectively. From the experiments of Fig. 5(d) and Fig. 6(d) we can see that, by utilizing the PCA method, the dimensions of CSI series can be reduced and the noise from the signals can be eliminated further.
(a) original CSI series of 10 sub-carries

(b) data after Mean filter

(c) data after Butterworth filter
Figure 5. shaking hands.

(a) original CSI series of 10 sub-carries

(b) data after Mean filter

(d) data after PCA
Summary
The contributions of our works are as follows. Firstly, we utilize traditional average filter algorithms to reduce noise of wireless signals and analyze their differences, which is effective to remove the environment noises. Secondly we use low pass filtering, such as Butterworth, to suppress the high frequency component of noise. Finally, we propose a principal component analysis (PCA) method based on feature extraction algorithm. PCA reduces dimensions of the CSI information obtained from the 30 sub-carriers and removes the uncorrelated noises. The experiments show that the filtered CSI information can be used to enhance the accuracy of the human activity recognition algorithms.

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References


