Through-the-Wall Human Behavior Recognition Algorithm with Commercial Wi-Fi Devices

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Abstract. Wi-Fi-based human behavior recognition technology is one of the research hotspots in the field of wireless sensing. However, the traditional Wi-Fi-based human behavior recognition algorithm does not consider the attenuation of Wi-Fi signals in the condition of wall barrier under complex indoor environments. As a result, the robustness of the Wi-Fi indoor human behavior recognition system is poor. In order to solve this problem, this paper proposes a Wi-Fi based behavior recognition algorithm through the wall. Firstly, the Wi-Fi signal distribution is analyzed according to the Wi-Fi signal model. Then, according to the distribution characteristics of different Wi-Fi signals, the principal component analysis (PCA) algorithm is used to reconstruct the signal to complete the de-nosing processing of the Wi-Fi signal. Finally, feature extraction and feature classification in the time-frequency domain is performed to complete the human behavior recognition. The experimental results show that the proposed algorithm has higher recognition accuracy in terms of walking and running than the traditional Wi-Fi based indoor recognition algorithms.

Keywords: Behavior recognition · Wi-Fi · Indoor environment · Principal component analysis (PCA) · Channel state information (CSI)

1 Introduction

In recent years, human behavior recognition technology has attracted much attention to monitor human behavior in indoor areas. Specific applications include health monitoring and fall detection for older people, scene detection, smart home and many other Internet-based of things (IoT) application. Human behavior recognition systems with different auxiliary equipment are mainly divided into three categories. The first category is a sensor-based human behavior recognition system [4], which requires the identified target to wear special equipment such as motion sensors, extracts the features of the data acquired by the sensor, and then uses the supervised learning algorithm to classify the characteristics of different behaviors. The system recognizes sleeping, sitting, walking, running, etc., with an accuracy rate of 90%. However, the identified target needs to carry the device at any time, so that the application range and recognition ability of the system are limited. In particular, in the case of the elderly forgetting

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to wear equipment, the consequences are unimaginable. The second category is a camera-based human behavior recognition system [1, 2], which performs well, but the main limitation is that behavior recognition must be performed under Line Of Sight (LOS) conditions. What's worse, the use environment of camera-based target behavior recognition systems is greatly limited due to sensitivity to light and privacy concerns. The third category is a passive detection system based on wireless signals [3, 5]. By extracting the characteristics of echo signals and constructing classifiers, the system realizes the behavior recognition of the identified targets, overcomes the safety hazards and limitations of scenarios of the first two types of human behavior recognition systems. It has obvious advantages in the field of human behavior recognition.

At present, as an important part of wireless signal-based passive detection system, the research of Wi-Fi-based behavior recognition system has been the focus of attention. Such systems include Wi-Fi access points (APs) and one or several receiving devices that support Wi-Fi protocols (such as 802.11n/ac) and are arranged in separate environments. When a person is active in the detection area, his or her behavior will have a certain degree of influence on the transmission environment of the Wi-Fi signal, and the channel state information (CSI) can finely record the change of the Wi-Fi signal. The system monitors the CSI information of the echo signals and extracts the signal characteristics of different actions, and then constructs the classifier to classify the behavior. Currently, the Wi-Fi-based behavior recognition system can identify walking, running, squatting and standing up and other actions, equipment cost is low, versatility, and recognition accuracy can reach 85%. But the environment has a greater impact on the system, especially in complex indoor environments with wall, cabinet and table, resulting in misjudgment of behavior.

For overcoming system stability degradation due to the complex indoor environment, this paper designs a Wi-Fi based through-wall human behavior recognition system, which filter out the interference caused by the wall, then the time and frequency domain characteristics of echo signal is extracted from the CSI information during the activity of the human body. Finally, the calculated behavior characteristics are used to construct the activity classifier to complete the behavioral judgment of the human behind the wall.

2 System Model

2.1 Channel State Information

Currently, CSI can be obtained by the NIC 5300 [6, 7]. CSI information can record the changes of Wi-Fi signals in a fine-grained manner. It has been widely used in human activity sensing areas such as personnel detection [13], behavior recognition [8–10], indoor positioning [14, 15], fall detection [12], etc. In addition, CSI can also be applied to micro-motion recognition. Perceptions of micro-actions such as gestures, lip movements [16], keystrokes [8], and heartbeats [18].

2.2 System Model

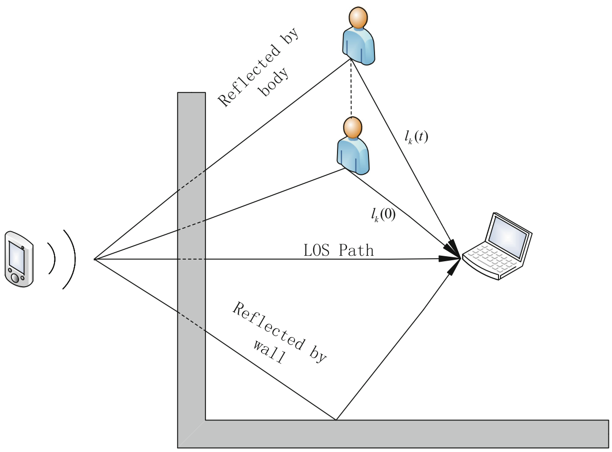


Fig. 1. A multipath signal model caused by human motion.

As shown as the Fig. 1, Wi-Fi signals have multipath effects in indoor environments and can propagate through multiple paths, including the LOS path and the path reflected by surrounding objects [11]. Assuming that the number of propagation paths is N, in the case of ignoring additive noise, different path gain $H(f,t)$ can be given as follows:

$$H(f,t) = e^{-j2\pi\Delta ft} \sum_{k=1}^{N} a_k(f,t) e^{-j2\pi f \tau_k(t)} \tag{1}$$

where $e^{-j2\pi ft_k(t)}$ represents the delay $\tau_k(t)$ of the Wi-Fi signal on the k^{th} path, and $e^{-j2\pi\Delta ft}$ is the phase due to the carrier frequency offset (CFO), $a_k(f,t)$ represents the initial gain of the k^{th} path, the initial gain of the signal will experience an inestimable attenuation after passing through the wall:

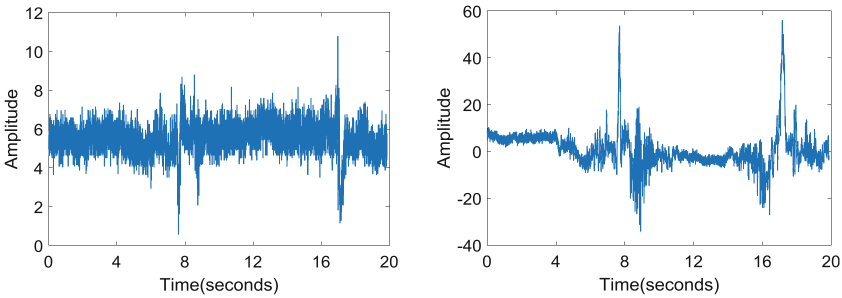
$$a_k(f,t) = \sigma_k b_k(f,t) \tag{2}$$

In the above formula, we ignore the phase offset caused by the sampling frequency offset, because we can effectively eliminate such errors in the subsequent noise reduction processing.

Changes in the length of a path lead to the changes in the phase of the Wi-Fi signal on the corresponding path. Consider the scenario in Fig. 1, where the Wi-Fi signal is reflected by the human body through the k^{th} path. When the human moves by a small distance, the length of the kth path changes from $l_k(0)$ to $l_k(t)$. The delay of the k^{th} path, denoted as $\tau_k(t)$, can be written as: $\tau_k(t) = d_k/c$, where c is the speed of light. Thus, the phase shift $e^{-j2\pi f \tau_k(t)}$ can be written as $e^{-j2\pi f d_k(t)/\lambda}$.

Theoretically, it is possible to accurately measure phase changes due to path changes, such as RFID systems [19], when receiving full synchronization. However, commercial Wi-Fi has a non-negligible CFO due to hardware defects and environmental changes. The center frequency drift is up to 100 kHz under the IEEE 802.11n protocol, and this frequency drift results in a fast CSI phase change. We observe that the CSI amplitude is not subject to severe interference with respect to phase, so we will use the CSI amplitude in subsequent work.

2.3 CSI De-nosing



(a) Original signal (b) De-nosing signal

Fig. 2. CSI de-nosing based on PCA

In the complex indoor environment, due to the influence of obstacles such as walls, the CSI amplitude information and phase information will be interfered, and the signal changes caused by the human body are relatively weak, so it is impossible to directly extract the signal variation characteristics caused by human activities such as Fig. 2(a). Therefore, this paper uses the PCA algorithm to cancel the interference, which caused by the hardware and wall in CSI information.

First, the CSI stream in the current sliding window is centered to eliminate the static components of the signal:

$$x_i = x_i - \frac{1}{n}\sum_{j=1}^{n} x_j \tag{3}$$

Then, the covariance matrix of the CSI stream is calculated and eigenvalue decomposition on the covariance matrix is performed to obtain the eigenvector of the covariance matrix. Finally, a new projection matrix is calculated by dimensional transformation to complete the target motion signal reconstruction:

$$Z_i = X^T w_i \tag{4}$$

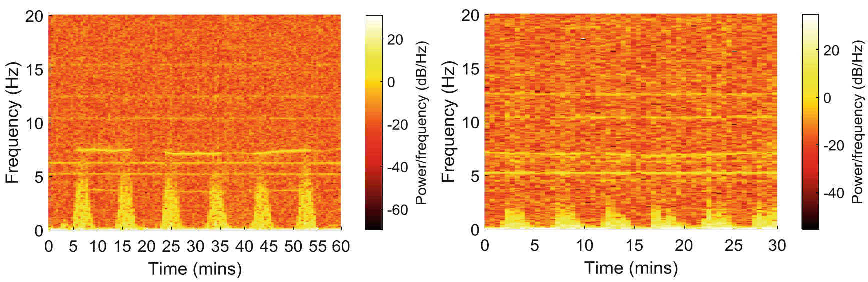
where w_i and Z_i are the i^{th} eigenvector and the main component of the i^{th} signal.

3 Behavior Recognition Through-the-Wall

3.1 Behavior Feature Extraction Based on Short Time Fourier Transform

Short-time Fourier transform (STFT) algorithm adds time domain window based on Fourier transform to avoid the shortage of traditional Fourier transform time domain information. Therefore, The choice of window is important because a shorter duration window will retain high frequency components and vice versa. In addition, since the window function value is typically very small or zero nearby its boundary, a portion of the windowed signal is ignored. Therefore, it is necessary to overlap these segments. The percentage of overlap depends on the window function. In general, 50% is a common value for overlap, and Fig. 3 shows the STFT spectrum of the two target activities of walking and sitting. The sampling frequency is 40 Hz, overlap 50%, and the window function uses the Hanning window function. The test time for walking and sitting is 60 s and 30 s, respectively. The test plan for walking is to walk for every 10 s, and the test plan for sitting is to sit every 5 s. It can be seen from the figure that the spectral frequency of walking is between 0 and 5 Hz, and the spectral frequency range of sitting is significantly smaller, ranging from about 0 to 2 Hz.

Therefore, we extract a spectrum with a length of 3 s, a frequency range of 10 Hz, and a total length of 210 as behavioral features.



（a）walking activity （b）sitting activity

Fig. 3. Spectrum of human activities

3.2 Behavior Classification

First, we use random forest with 100 trees for classification of activities. To have a feature vector that contains enough information about an activity, the modified STFT bins are stacked together in a vector for every 3 s of activity. Hence, every feature vector will be of length 210. We also implement other techniques such as SVM, logistic regression, and decision tree; however, the random forest outperforms these techniques. We observe that decent performance can be obtained for some of the activities, but not for activities such as “Sit down” and “Stand up”.

4 Implementation and Evaluation

4.1 Implementation

We use a Mini PC with an Intel 5300 Wi-Fi card as the receiver and transmitter. The CSI values obtained from the regular data frames are sent by the AP, and we install the CSI tool developed by Halperin et al. All experiments in the 5.5 GHz band with channels, the bandwidth is 20 MHz. We choose the 5.5 GHz band for two reasons: first, the 5.5 GHz band has shorter wavelengths, which results in better range resolution; second, it has less line interference than the 2.4 GHz band.

We collect training samples for eight different activities in the lab environment with 6.5 m in length and 7 m in width, shown in Fig. 4. Our activity data contains 420 samples performed by 6 volunteers who are 4 male and 2 female graduate/ undergraduate students. The specific behavior is shown in Table 1.

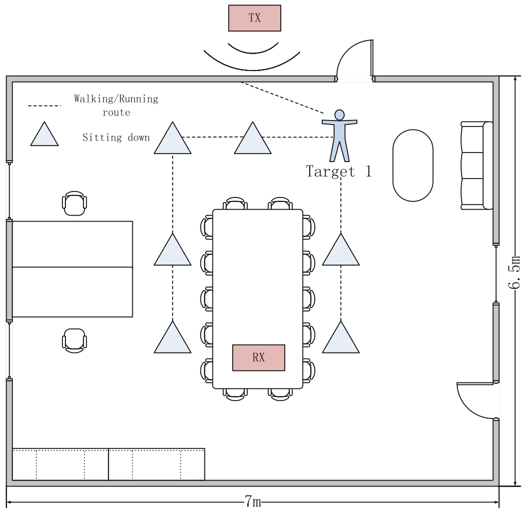


Fig. 4. Test environment

Table 1. Activity dataset

Activities	Training samples	Test samples
(R) Running	105	85
(W) Walking	120	95
(SD) Sitting down	75	60
(SU) Standing up	75	60

4.2 Evaluation

The experimental results are shown in Fig. 5. Among them, the two movements of walking and running can reach the accuracy of more than 90%, but the recognition accuracy of the two movements of standing up and sitting down is not ideal. At the same time, the experimental results show that the Wi-Fi-based behavior recognition through the wall method is effective.

	Walk	Run	Sit down	Stand up
Walk	0.95	0.04	0.01	0
Run	0.06	0.92	0.01	0.01
Sit down	0.02	0.03	0.68	0.27
Stand up	0.04	0.02	0.31	0.63

Fig. 5. Confusion matrix

5 Conclusion

Aiming at the problem of signal attenuation caused by wall blockage in Wi-Fi signal in complex indoor environment, this paper proposes a Wi-Fi based post-wall target behavior recognition method. Firstly, the PCA algorithm is used to eliminate the interference caused by the wall and hardware. Then, the behavior characteristics are extracted by STFT algorithm. Finally, the classification of target behavior is completed according to the random forest algorithm. However, although the proposed behavior recognition method can effectively improve the accuracy and stability of Wi-Fi indoor identification, how to solve the problem of distinguishing similar actions will be considered in the future.

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