Device-Free Stationary Human Detection with WiFi in Through-the-Wall Scenarios

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Abstract. Human detection plays an important role in smart home and health monitoring. WiFi-based device-free detection schemes are widely proposed. The current WiFi-based device-free through-the-wall human detection system can detect moving human behind wall by the theory that RF signals would fluctuate remarkably when objects move within the area of interests, and remain stable in the case of no motion interference. However, stationary human detection is still an open issue, because it is hard to capture the fluctuate of signal caused by the weak movements (such as breathing, writing, etc.) of stationary human behind wall. In order to solve this problem, this paper proposes a novel system which extracts more delicate features for detection. The proposed system extracts features from time of fly (ToF) of signal, and then trains a neural network to classify these features to determine if a stationary human behind the wall. Our experiment shows that the detection accuracy of proposed system can reach 87.7% in typical office environment.

Keywords: Device-free · WiFi · Stationary human detection · Channel state information

1 Introduction

Different from conventional device-based schemes, recent development in wireless techniques have spurred an emerging development of device-free sensing techniques, which utilize pervasive WiFi signal to sense human state without attaching any device to users. Device-free means that detect human in the area of interests without attaching any device to them, which is closer to the actual application in our daily life. The typical applications include indoor localization [1], activity recognition [2], even gesture recognition [3], etc. Existing human detection schemes can be divided into two types: wall-through and wall-free. In [4], a unified framework for simultaneous detection of moving and stationary people proposed. The moving and stationary human are detected by using correlation of signals in the time domain and exploiting chest motions of human breathing as an intrinsic indicator. However, the through-the-wall scenario is not considered. In [5], different from utilizing the correlation of channel state information (CSI) in the time dimension, the correlation of the WiFi signal subcarriers is used to detect the moving human behind wall, which is not available for

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stationary humans. Based on all the references above-mentioned, stationary human detection in the through-the-wall scenario is not considered for two main reasons: (1) the signal-to-noise ratio becomes lower when signal going through the wall; (2) the fluctuate of signal caused by stationary human is too week to capture.

In order to overcome these challenges, this paper proposes a novel detection system. At first, we introduce a linear transformation to reduce the noise of phase. Then, based on the available phase information, we estimate time of fly (ToF) of signal by using the smooth MUSIC algorithm, and calculate the variance of ToF of each path over a period of time as a feature. Finally, we trained a neural network classifier to classify the extracted features effectively. Experimental results show that the proposed system can achieve an overall recognition accuracy of 87.7%.

2 Stationary Human Detection System

2.1 Overview of System

The proposed system is a device-free system that can detect stationary human behind wall by using ubiquitous off-the-shelf Wi-Fi devices, which consists of a transmitter with one antenna and a receiver with three antennas. The transmitter and receiver are separated by a wall. The data processing flow of our system is shown in Fig. 1. At first, after receiving CSI from transmitter, the receiver will provide the CSI to data processing module, where a linear transformation will be implemented to reduce the noise of phase. Then, the processed CSI are used to estimate ToF, from which features are extracted for stationary human detection. Finally, we use neural networks to classify the extracted features to identify the stationary person behind wall. The details of each module will be introduced in the following sections.

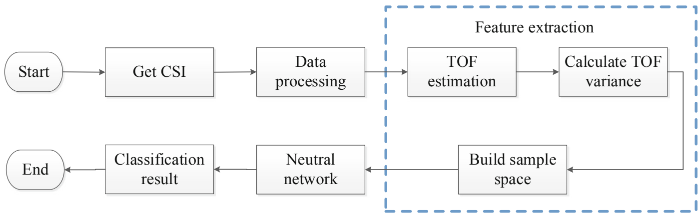

Fig. 1. The data processing flow of system.

2.2 Data Processing

In this section, we introduce a linear transformation which can reduce the noise of phase. Each packet consists of CSIs from 30 subcarriers, whose structure is shown as:

$$H = [H(f_1), H(f_2), H(f_3), \ldots, H(f_{30})] \tag{1}$$

Each CSI describes the amplitude and phase information of a subcarrier, which is expressed as:

$$H(f_i) = \|H(f_i)\| e^{j\,\sin\{\angle H(f_i)\}},\ i \in [1, 30] \tag{2}$$

where $H(f_i)$ represents the CSI of i^{th} subcarrier which the central frequency is f_i, and $\angle H(f_i)$ represents the phase of each subcarrier. Synchronization error between transmitter and receiver cannot be eliminated completely and the existence of synchronization error has a great influence on the phase. Thus, the phase can be represented as:

$$\tilde{\Phi}_j = \Phi_j + 2\pi \frac{j}{k} \varphi_\varepsilon + \beta \tag{3}$$

where φ_ε is the clock synchronization error, and k represents the total number of subcarriers. β is the constant phase error. $\tilde{\Phi}_j$ and Φ_j represents the measured value of phase and the real phase, respectively. We employed one kind of linear transformation to eliminate the clock synchronization error and phase shift [6].

In order to eliminate φ_ε and β, we calculate the approximate slope and intercept of phase. After eliminating φ_ε and β, the phase can be written as:

$$\hat{\Phi}_{ji} = \tilde{\Phi}_{ji} - (ak_i + b) \tag{4}$$

where a is the slope and b is the intercept. When the subcarrier index is symmetric, the sum of subcarriers is zero. Then, the phase after transformation is shown as:

$$\hat{\Phi}_{ji} = \Phi_{ji} - ji\frac{\Phi_{jn} - \Phi_{j1}}{jn - j1} - \frac{1}{n}\sum_{k=1}^{n} \Phi_{jk} \tag{5}$$

where n is the number of subcarriers. After this process, we can obtain the approximate and available phase for next section.

2.3 Feature Extraction

A multipath channel model can be established for each subcarrier by utilizing the CSI measurement matrix obtained on one receive antenna, shown as:

$$\begin{bmatrix} csi_1 \\ csi_2 \\ csi_3 \\ \vdots \\ csi_{30} \end{bmatrix} = \begin{bmatrix} e^{-j2\pi f_1 \tau_1} & e^{-j2\pi f_1 \tau_2} & \cdots & e^{-j2\pi f_1 \tau_L} \\ e^{-j2\pi(f_1 + \Delta f)\tau_1} & e^{-j2\pi(f_1 + \Delta f)\tau_2} & \cdots & e^{-j2\pi(f_1 + \Delta f)\tau_L} \\ e^{-j2\pi(f_1 + 2\Delta f)\tau_1} & e^{-j2\pi(f_1 + 2\Delta f)\tau_2} & \cdots & e^{-j2\pi(f_1 + 2\Delta f)\tau_L} \\ \vdots & \vdots & \ddots & \vdots \\ e^{-j2\pi(f_1 + 29\Delta f)\tau_1} & e^{-j2\pi(f_1 + 29\Delta f)\tau_2} & \cdots & e^{-j2\pi(f_1 + 29\Delta f)\tau_L} \end{bmatrix} \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \\ \vdots \\ \alpha L \end{bmatrix} \tag{6}$$

where $csi_k,\ k \in [1, 30]$ is the k^{th} subcarrier of the received signal, f_1 is the frequency of the first subcarrier, and L represents the total number of signal propagation paths. Δf is carrier spacing. $\tau_i,\ i \in [1, L]$ and $\alpha_i,\ i \in [1, L]$ represent the ToF and path coefficients of the i^{th} path arriving at the antenna, respectively.

Let $\mathbf{X} = [csi_1 \quad csi_2 \quad \cdots \quad csi_{30}]^T$, and the smooth MUSIC algorithm [7] is used to complete the estimation of TOF. The autocorrelation matrix of the matrix $\mathbf{X}$ can be expressed as:

$$\mathbf{R_{xx}} = E(\mathbf{XX^H}) \tag{7}$$

Assume that the real data matrix is statistically uncorrelated with the noise matrix. Then the matrix $\mathbf{R_{xx}}$ can be divided into signal subspace and noise subspace. Define spectral functions as:

$$p(\tau) = \frac{1}{\mathbf{a^H}(\tau)\mathbf{GG^H a}(\tau)} \tag{8}$$

where $\mathbf{a}(\tau) = \begin{bmatrix} 1 & e^{-j2\pi\Delta f\tau} & e^{-j2\pi 2\Delta f\tau} & \cdots & e^{-j2\pi 29\Delta f\tau} \end{bmatrix}^T$ denotes the steering matrix and $\mathbf{G}$ stands for the eigenvectors corresponding to noise subspace.

For combating the coherent signals, smoothing on $\mathbf{XX^H}$ is performed before decomposition, as shown in Fig. 2. We assume that the total number of subcarriers is M and the number of subcarriers in the subarray is N, then the number of subarrays is $M - N + 1$. After smoothing, autocorrelation matrix can be expressed as:

$$\mathbf{R}_{smooth} = \frac{1}{N - M + 1} \sum_{i=1}^{N-M+1} \mathbf{R}_i \tag{9}$$

Then, we can get the spectral function by $\mathbf{R}_{smooth}$. Perform a traversal search on τ. When the search τ is equal to the ToF of the signal propagation path, a peak will appear on the spectrum. In fact, due to the existence of packet detection delay (PDD), all paths generate a common additional delay, which is much larger than the TOF of normal indoor signals. It has no effect on feature extraction, although the estimated ToF is not the true value. Because we use the stability of ToF over a period of time as feature.

Select the ToF of the four paths with the strongest energy to represent the TOF of all paths between the transceivers, and calculate the variance of each path over a period of time (2 s) as a feature. There are three receive antennas, and a total of twelve feature can be obtained.

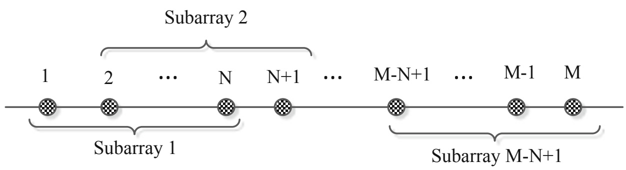

Fig. 2. There is a total of M subcarriers, and each subarray has N subcarriers. After smoothing, $M - N + 1$ subarrays can be obtained.

2.4 Neural Networks Based Detection

Based on the obtained features, a trained neural network is used to complete the recognition. Neural network consists of three parts: input layer, hidden layer, and output layer. Input layer neurons are used to receive external input, Hidden layer and output layer neurons process the signal, and the final result is output by the output layer neurons. The learning process of neural network is to adjust the connection weight between neurons, and change the threshold of each function neuron according to train data. When the appropriate connection weigh and threshold are obtained, the learning process will converge [8].

In our system, after parameter tuning, we design a 3-layer neural network with ten hidden layer neurons. We use the twelve features mentioned above as the input features of the samples. Two features, nobody behind the wall and stationary people behind wall, are used as output features. Our network structure is shown in Fig. 3. We randomly select 60% of the samples as training samples to train a classifier, then use remaining samples as test samples to verify the accuracy of the classification.

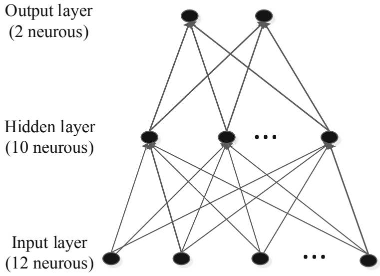

Fig. 3. The designed 3-layer neural network has 12 neurons in input layer, 10 neurons in hidden layer, and 2 neurons in output layer.

3 Experiments Evaluation

3.1 Implementation

The proposed system contains a transmitter and a receiver both equipped with the Intel 5300 wireless NIC, and the parameters setting is shown in Table 1.

Table 1. Parameters setting.

Parameters	Transmitting AP	Receiving AP
Mode	Injection	Monitor
Channel number	149 (5.745 GHz)	
Bandwidth	40 MHz	
Channel sample rate	500 times per second	
Number of subcarriers	30	
Index of subcarriers	[−58, 54, …, 54, 58]	
Transmit power	15 dBm	

The transmitter has one antenna and the receiver equipped with three antennas. Meanwhile, in order to reduce the noise interference, we accomplish the experiments with the help of directional antenna at the transmitter. All the experiments are conducted in a typical office as shown in Fig. 4. A volunteer is located at the position marked by pentagram in the picture in experiments. We collect data of two categories: no human in the monitored room and stationary human in the monitored room.

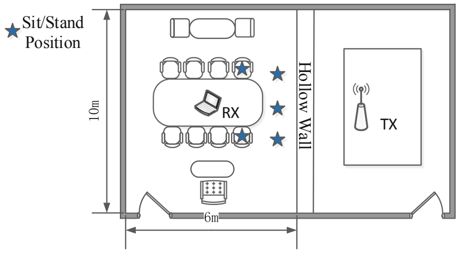

Fig. 4. Floor plan of the experimental areas.

3.2 Spectrum Analysis

In this section, we analyze the value of ToF over time domain. Figure 5 shows the change of ToF over time when nobody is behind wall and stationary human is behind wall. It can be observed that the change of ToF is relatively stable when no one is behind wall, while there are many obvious jitters when stationary human is behind wall. This difference is caused by the fact that the signal propagation paths is relatively stable when there is no man in the room. When a stationary human in the room, the slight action (such as breathing, writing, etc.) will interfere the signal propagation paths, and then changes the propagation time of the signal on the paths.

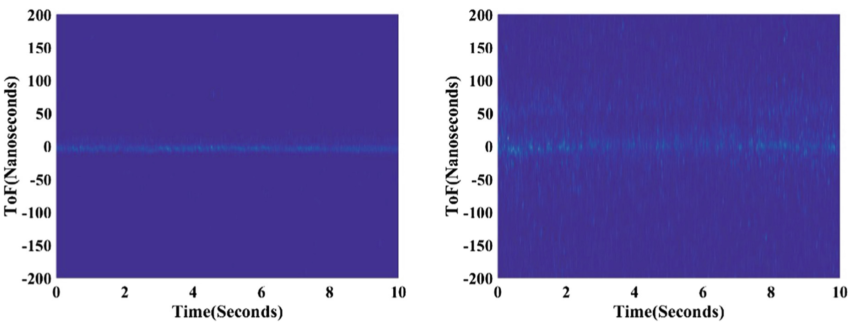

Fig. 5. The change of ToF over time. (a) shows the change of ToF over time when no one is behind the wall. (b) shows the change of ToF with time when there is a stationary person behind the wall.

3.3 Detection Accuracy Analysis

We obtain a total of 3867 samples, including 1786 no human samples and 2081 stationary human samples. Stratified sampling is used to randomly select 60% of the samples from the total samples as the training data of the neural network, and the remaining 40% of the samples are used as the test samples.

The detection accuracy of the test samples is shown in Table 2. As seen, most human absence samples are accurately categorized as human absence and only small portion of 7.8% is labelled as stationary human. 85.0% of stationary human samples are correctly classified. The overall recognition accuracy is 87.7%. This accuracy rate is satisfactory, indicating that the proposed system is an effective solution to detect stationary human in through-the-wall scenarios.

Table 2. Detection accuracy.

Output class	Target class	
	Stationary human	Human absence
Stationary human	92.2% (523 samples)	7.8% (44 samples)
Human absence	15.0% (129 samples)	85.0% (732 samples)

4 Conclusion

In this paper, we propose a device-free through-the-wall stationary human detection system based on channel state information. First, we introduce a linear transformation to reduce the noise of phase. Then, we estimate the ToF of the signal using the smooth MUSIC algorithm, and calculate the variance of ToF of each path over a period of time (2 s) as a feature. Finally, a trained neural network is used to complete the recognition. Experimental results show that the proposed system can achieve an overall recognition accuracy of 87.7%, which makes it possible to detect stationary people in through-the-wall scenarios, and expands the application range of WiFi-based device-free detection system.

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