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Human Movement Detection and Gait Periodicity Analysis Via Channel State Information

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In recent years, movement detection and gait recognition methods using different techniques emerge in an endless stream. On the one hand, wearable sensors need be worn by the detecting target and the method based on camera requires line of sight. On the other hand, radio frequency signals are easy to be impaired. In this paper, we propose a novel multi-layer filter of channel state information (CSI) to capture moving individuals in dynamic environments and analyze his/her gait periodicity. We design and evaluate an efficient CSI subcarrier feature difference to the multi-layer filtering method leveraging principal component analysis (PCA) and discrete wavelet transform (DWT) to eliminate the noises. Furthermore, we propose the profile matching mechanism for movement detection and the gait periodicity analysis mechanism for human gait. Experimental results in different environments indicate that our approach performs identification with an average accuracy of 94%

Keywords: Channel State Information, Moving target detection, Subcarrier Feature Difference, PCA , DWT, Gait Periodicity Analysis

1. INTRODUCTION

The detection and analysis of human behavior in indoor environment significantly increased over the recent years [1]. Typical applications include human detection for intruder detection [2], human behavior recognition [3], and children and elderly monitoring in home [4]. The human body movement detection method based on specific hardware has been used widely (e.g., accelerometer, camera [5], pressure sensor [6], infrared sensor, etc.). Those methods are subject to invasive sensing or vision constraints, which limit their widespread applications. With commodity Wi-Fi devices and the prevalence of Wi-Fi network infrastructures, the RF-based method attracts much attention from industry and academia [7-9].

Researchers use the commercial off-the-shelf Wi-Fi infrastructures to detect human behaviors or activities. It naturally has two advantages. One is that Wi-Fi signals are widely available in indoor environments and low-cost to use. Another is Wi-Fi signals provide an information carrier of human activity through the signal feature such as Received Signal Strength (RSS) and Channel State Information (CSI) [10]. However, RSS has a very low resolution and stability. When there are little changes in the environment, the RSS will have a great variety. So it will cause a high false positive rate and false negative rate. Furthermore, RSS only expresses the mixed energy information of the received data packets. Due to the indoor multipath effect, the deviation of RSS cannot be prevented. To obtain more fine-grained multipath information, researchers turn their attention to CSI on orthogonal frequency division multiplexing (OFDM). CSI is widely used for its powerful anti-jamming performance. CSI can record the environment feature from the carrier level, and it is highly sensitive to capture the environment changes. Moreover, CSI can present different amplitude and phase characteristics for different propagation environments, while the overall structural features may be relatively stable in the same propagation environment [10]. Because signal will be inevitably affected by various factors, such as random noise, narrow band interfer-

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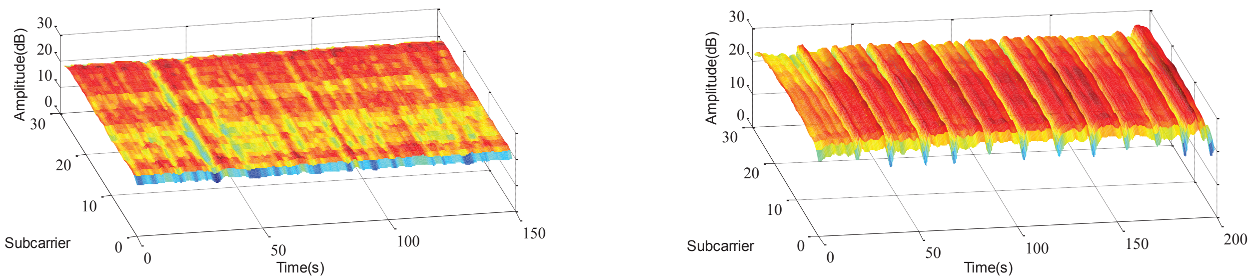


(a) CSI streams of static state (b) CSI streams of squatting behavior

Figure 1 CSI sensitivity analysis.

ence etc., in the process of signal acquisition and transmission. However, the existing human detection approaches with CSI are unable to be directly used in our human detection. Traditional filters such as low-pass filters or median filters do not perform well in removing the impulse and burst noises [3]. Therefore, it is a challenge to extract robust features from CSI in multifarious noises. Another challenge is that when there are some other exchanges caused by additional moving objects (e.g., fluttering of curtains, movement of a cat etc.) may also disturb the analysis of CSI signals. It may result in decreasing the detection accuracy and increasing the false alarm rate. Therefore, can we solve this complicated phenomenon to improve the accuracy of human detection for intruder detection?

We handle these challenges by first introducing the multi-layer filtering framework based on principal component analysis (PCA) and discrete wavelet transform (DWT) to eliminate noises. Furthermore, the two-dimensional CSI frames are built using the signal amplitude for extracting feature of CSI subcarriers. After these preprocessing, the subcarrier feature difference with CSI as the profiling mechanism to detect when there are moving targets. If there is a moving target, the gait periodicity of human walking is analyzed by autocorrelation to assist intruder detection. The gait periodicity analysis is to distinguish if the moving target is human who is regarded as an intruder. Our method is implemented on the commercial Wi-Fi devices and its performance is evaluated in two typical indoor environments: laboratory (NLOS, rather complex multipath environment) and visiting hall (LOS, rather sparse multipath environment). The results show that the average accuracy of our method can approach 94% using a pair of sender and receiver in the real environment.

The contributions are summarized as follows:

1. We introduce the multi-layer filtering framework based on PCA and DWT to get clean CSI from collected polluted CSI data.

2. We investigate the wireless signal feature impacted by human. By exploiting the sensitive disparity of CSI subcarriers to human behavior, we examine the challenges of using wireless for detecting if there are moving targets in the environment.

3. The gait periodicity is analyzed according to the autocorrelation of walking CSI signals. We design and implement our method with commercial hardware and evaluate its performance. The results of experiments indicate the effectiveness of the method.

In the rest of this paper, we first briefly present existing human activity recognition efforts in Section 2. Then we will present the multi-layer filtering framework and moving target detection in Section 3. Section 4 and 5 elaborates the gait periodicity analysis in and evaluates its performance respectively.

2. RELATED WORK

In this section, we describe the state of the arts. The technologies of activities recognition can be divided into four categories: video based, specialized hardware based, radar based and wireless signals based.

Video Based. Utilizing cameras, researchers in the area of computer vision deal with the problem of human activities recognition by images processing [1]. All these methods rely on visual range of the camera and image quality. However, since cameras are limited in line-of-sight (LOS), some blind areas will exist. Cameras are easily to be blocked by the smoke and so on. And it has a certain request to the light [5]. The most important is that the camera is unable to be placed in private space. The Wi-Fi signals can avoid the burden of privacy.

Specialized Hardware Based. Wisee [11] recognizes a set of nine different gestures using USRP to get the OFDM signals. WiHear [12] identify the pronunciation using special directional antenna to get the effects on CSI due to the movement of lips. But WiHear does not have an effective method to eliminate the noises in CSI streams, so it must use a special directional antenna to achieve acceptable accuracy. Allsee [13] recognizes gestures using a special designed analog circuit to extract the amplitude of the received signals. In comparison, our method requires no specialized hardware and achieves high accuracy at the same time.

Radar Based. Radar technology requires ultra-wideband transmissions with GigaHertz of bandwidth [14, 15], while Wi-Fi technology requires narrow bandwidth of 20MHz. Furthermore, radar technology adopts tailor-made transmissions to perform images, such as Frequency Modulated Continuous Wave (FMCW) [16]. While the Wi-Fi based adopts OFDM modulation which is used to communication. To use the ubiquitous Wi-Fi signals to achieve our purpose with low cost than to use Radar. Such systems are called as Wi-Fi radar.

Wireless signals based. In the literatures, researchers leverage wireless signals to recognize human activities such as falling [4], and exploit the rhythm of human activities to achieve detection and recognition [2,17]. In [2], the periodicity of weak human breathing pattern was used to detect static person in indoor environment. In [17], profiting from the rhythm of smoking activity, the smoker was detected. Since wireless signals may be reflected differently with the different human activities, numerous efforts have used wireless signals to detect moving targets [18,19], or hand gestures [20] and daily activities [3]. In [21,22], the authors use the eigenvalue change of correlation matrix of CSI in different time to detect moving individuals. However, this kind of feature has a great restriction to the behavior of intruder. In other words, such feature can be used only when people are very close to the computer or AP in the line-of-sight (LOS) [23]. In this paper, CSI subcarrier feature difference and the gait periodicity analysis are used to detect moving targets.

3. MOVING TARGET DETECTION

It is known that the environment changes such as the moving of human can affect the communications between both wireless devices. The phenomenon can be utilized to device-free intrusive detection and human behavior recognition and localization [24]. This section first presents the CSI sensitivity to human behavior by comparing CSI state in static and dynamic environments. Then we present the design of our method in moving target detection. And the details on gait periodicity analysis are in the next section.

3.1 CSI sensitivity analysis

As wireless sensing environments, wireless signals can detect obstacles in the environment taking advantage of LOS or NLOS propagation using the signal arrival time [25]. Human movements enable be considered as moving obstacles, which changes the transmission of Wi-Fi signals. An important observation is that different activities have different influence on CSI amplitude. As shown in Figure 1, CSI is very sensitive to human behavior. CSI streams not only change with the behavior but also can be seen that the CSI streams are correlated. Different CSI subcarriers have the similar peaks and troughs.

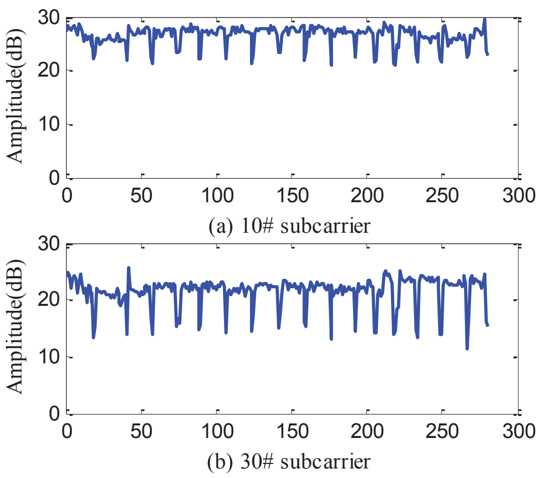


Figure 2 Sensitivity analysis of different subcarriers.

Moreover, . See as figure 2, which demonstrates CSI streams of squatting behavior on 10# subcarrier and 30# subcarrier. We can observe that the 30# subcarrier is more sensitive than the 10#. The similar phenomenon exists in the other subcarriers. It is also noticed that different subcarriers are distinguished to different parts of human body in sensitivity. Some may have sensitivity to arms, other may to legs. Thus, different subcarriers may contain different information at the same time. Moreover, the sensitivity of CSI single subcarrier to behavior is unstable and changes with time. Due to the individual behavior is different and various. The intruder will not maintain the same posture all the time. Posture change will lead to alter in the sensitivity of subcarriers to individual behavior.

It is not wise to use all the subcarriers due to their high correlation. To use the best subcarrier requires selection in advance. Furthermore, sensitivity of the best subcarrier is dynamic. Stated thus, it requires detailed design that how to extract human behavior information from the time-varying and independent subcarriers.

3.2 Noise reduction

It is known that noise as an interference signal is ubiquitous, such as random noise, narrow band interference etc. In the process of getting CSI and transporting signals, CSI signals can be influenced by various noise signals, namely raw CSI. The information we got includes the meaningful information which can analysis the moving target and various noise signals. They are not reliable on detecting moving target directly. Even in the static environment, the CSI can be also influenced by electromagnetic noise.

How to extract meaningful information from raw data becomes one of the key issues about transforming them into clean data. The data collected by receiver are susceptible to random noise and other factors in the environment. There are deviations in the measurements, even though in same conditions. Denoising can improve both quantity, accuracy and efficiency of data analysis.

Traditional filters such as low-pass filters or median filters do not perform well. Low-pass filters can not distinguish between the meaningful signals and noise signals in high frequency. Low-pass filters allow to getting signals which are below the cut-off frequency. The signals which are over the cut-off frequency will be passed. Due to meaningful signals generally performance as low frequency signals, noise signals generally performance as high frequency, so we can use low-pass filters to eliminate noises. But when there are high frequency human activities in the environment, such as falling, low-pass filters will do not perform well.

The principle of Median filters is taking the average value of N subsampling data as filtering result. It works for filtering the random noises, but does not work for burst pulse. Traditional filers may cause signal distortion and false positives to a certain extend. Therefore, it is a challenge to extract robust features from the raw CSI considering all kinds of noises. In this paper, we benefit from PCA and DWT to propose the multi-layer filtering framework.

PCA can preserve the main features of the original signals to a certain extent. The selection of principal components is based on the cumulative contribution rate. The number of principal components used for feature extraction is empirically chosen to achieve a good tradeoff between classification performance and computational complexity. Due to the very high correlation of subcarriers, the noise will be captured in the first principal component along with the human motion signals [3]. So the use of PCA cannot eliminate the noises effectively. The contribution rate of the first principal component is very large in our experiments. If we discard the first principle component, it will lose some information and lead to signal distortion.

The filter based on DWT can obtain the CSI at multiple resolutions on multiple time scales. CSI signals are decomposed into approximate signals and detail signals by DWT. It can preserve extremely well the sharp transitions in signals than the other low-pass filters. But it also exists two problems. First, the resolution of wavelet transform classifier is 2^j times. Therefore, the processing effects are not very ideal for some cases. Second, there may appear obvious and regular non-uniform effect with the increase of decomposing levels, and the loss will affect the final signals. For human recognition, we should extract the real information of the feature.

PCA can provide the principle components of CSI signals. CSI signals can be decomposed into detail component and high frequency component by DWT. We think this question: can we fuse PCA and DWT to get main features of CSI signals avoiding the disadvantages of using PCA and DWT individually at the same time? As shown in Figure 3, we extract principal components of CSI streams with PCA firstly. But we discard the first principal component and remain the other principal components. The reasons are as follows. On the one hand, noises are captured in the first principal component along with the human movement signals [3], CSI sequence can be decomposed into approximate components and detail components by DWT. On the other hand, the noises are generally expressed as high frequency signals, which inspires us to discard the detail components. Secondly, we fuse the low frequency component produced by DWT and the second principal component with the wavelet transform fusion algorithm. The new second principal component is obtained. Finally, we fuse the principal components by PCA inverse transform. The final composite signals are called clean CSI.

3.3 Model Formulation

CSI frame. We first turn clean CSI sequences into CSI frames. As shown in Figure 4, we partition time into consecutive CSI frames. In Figure 4, time window length T is 40 s, containing $40 \times 30 = 1200$ pixels. The pixel $P_{m,n}$ in a frame is the CSI amplitude of subcarrier m collected in the n-th time t_n.

Extract CSI subcarrier feature difference. Human detection requires a feature which is independent of the power and is related to the change of CSI, due to the power parameters of the wireless device can be varied adaptively in different scenarios. Variance can not only automatically and accurately detect static and dynamic environment, but guarantees the algorithm rapid convergence in a variety of environments.

The variance of amplitude in sliding window ω can be written as:

$$Var(P_{m,\omega}) = \frac{1}{\omega}\sum_{i=1}^{\omega}[P_{m,i} - \frac{1}{n}\sum_{i=1}^{n} P_{m,i}]^2 \tag{1}$$

Feature difference can be written as:

$$\begin{aligned} d = \max[&Var(P_{1,\omega}) - Var(P_{1,\omega-1}), \cdots, Var(P_{m,\omega}) \\ &- Var(P_{m,\omega-1})] \end{aligned} \tag{2}$$

Differential analysis is performed on two adjacent sliding windows in all the subcarriers. We will get a matrix D with the sliding window:

$$D = \left\{d_1, d_2, \cdots, d_{\frac{n}{\omega}-1}\right\} \tag{3}$$

3.4 Moving Target Detection

Passive detection is generally used in two ways: clustering based and threshold based. The former clusters the CSI data into several clusters, and then by comparing the distance of the cluster centers to distinguish different states (presence or absence of human). The latter is based on the pre-collected data to find a general threshold, and conducts state identification based on the threshold value. Although the clustering method avoids both environment calibration and threshold training, it requires that at least two states are involved in each group of measurements, otherwise, one cluster or several clusters corresponding to a same state are resulted, which leads to false detection. In this paper, we use clustering method to model, and intrusion behavior was detected by threshold method.

First we use threshold method to coarsely decide whether there is a moving person. If the answer is yes, we will do finer grained human detection. The threshold method can be written as:

$$D = \left\{d_1, d_2, \cdots, d_{\frac{n}{\omega}-1}\right\} \leftrightarrow \theta \tag{4}$$

Where θ is threshold, if feature difference in window ω is greater than θ, there is a moving target. Then we will enter the phase of gait periodicity analysis. In this paper, we use SVM to classify the CSI data into two clusters with the semi-supervised learning method. It can also be used adaptive update data base based on user feedback.

SVM and neural network can both be used for pattern recognition, but SVM can effectively solve the finite sample data model construction compared with the neural network, and has advantages such as strong generalization ability, convergence to the global optimum and insensitive to dimensions and so on. So SVM is used in this paper to classify if there have moving targets. The decision function can be written as:

$$d\,(x) = sgn\,(< w, x > +b) = sgn\left(\sum_{i=1}^{l} a_i a_j < x, x_i > +b\right) \tag{5}$$

We frame this as a best subset selection problem:

$$\arg\max_{x} \frac{1}{2}\sum_{i,j=1}^{l} y_i y_j a_i a_j < x_i, x_j > \text{ s.t. } \sum_{i=1}^{l} a_i y_i = 0 \tag{6}$$

Where $a = [a_1, a_2, \cdots, a_l]^T$, $a_i \geq 0$ is Lagrange multiplier; $w = \sum_{i=1}^{l} y_i a_i x_i$ is weight vector which can achieve the best classification interval of the optimal hyper plane.

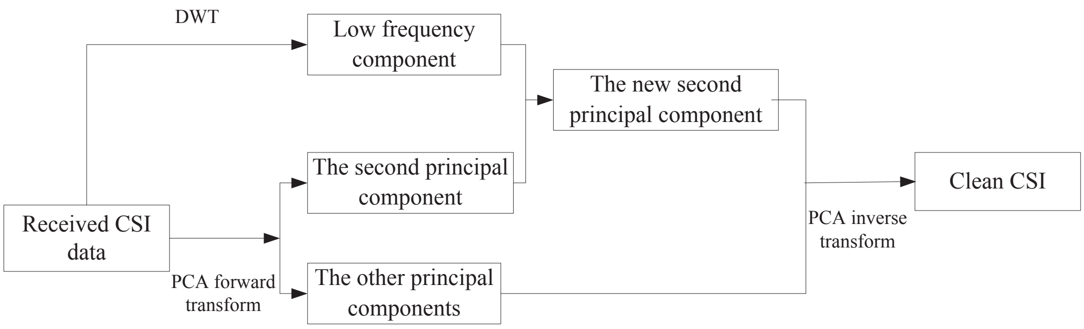


Figure 3 The multi-layer filtering framework based on PCA and DWT.

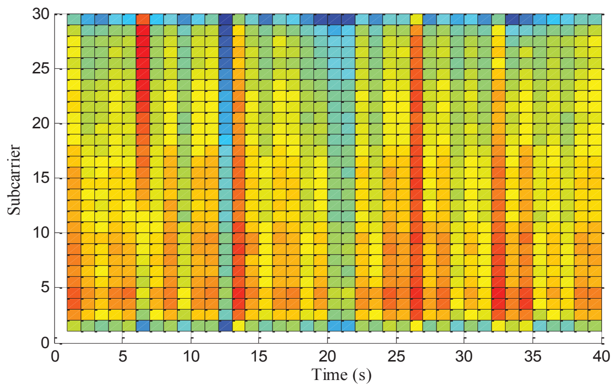
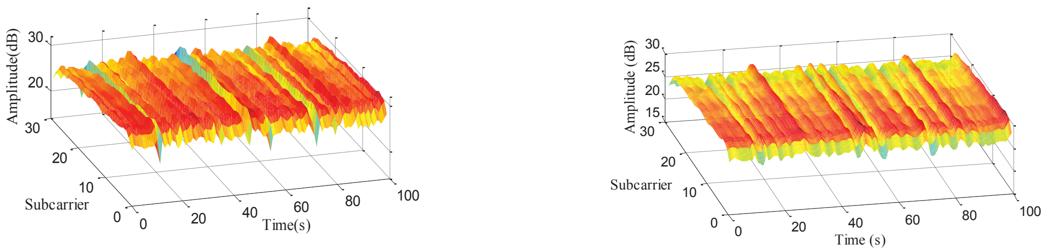


Figure 4 Constructing CSI frames from CSI sequences.



(a) Raw CSI measurements with walking

(b) Conspicuous repetitive patterns over all subcarriers of filtered CSI

Figure 5 Rhythmic motions of human walking induce wave-like patterns on the received signals. Various colors in (a) and (b) indicate different level of signal strengths, decreasing from red to blue.

4. GAIT PERIODICITY ANALYSIS

This section prevents the detail analysis of gait periodicity. After the moving target detection, there are difficulties in distinguishing if the moving target is human or if the human is an intruder. Because the fact that CSI can also be influenced by other factors, such as fluttering of curtains, movement of a cat etc. Therefore, we analyze gait periodicity of walking to assist moving target detection with the purpose of improving detection accuracy.

4.1 Analyzing Gait Periodicity

In typical indoor environments, propagation paths of wireless signals can be easily affected by human bodies and other obstacles. Therefore, the human walking movement is the equivalent of a moving obstacle. And signals can be potentially modulated by periodic walking if it interacts with the person. When there is a moving target, the received signals can be continuously affected by reflecting form the moving legs. Intuitively, a human's walking is a periodical action with uniform pace. The motions of human walking induce wave-like patterns on the received signals are shown in Figure 5 (a). The noises in CSI pattern are obvious as we can see. The former denoising method is not work due to the temporal correlation and the frequency correlation is needed.

In this paper, first, we filter out the irrelevant components, such as burst noise and other motions, by applying a band-pass filter. Then we use interpolation fitting to construct the CSI sequence. When the transmitter sends packets to the receiver, the collected data on receiver are non-uniformly. Because the equipment can not make the transmitter and receiver get packets with the same rate. There are packet losses, time delay, transmission delay and other processing delays. Therefore, it is necessary to adopt interpolation fitting for further analysis and it make the CSI data more plentiful and increasingly easy to analysis the periodicity. The conspicuous repetitive patterns over all subcarriers of filtered CSIs are shown in Figure 5 (b).

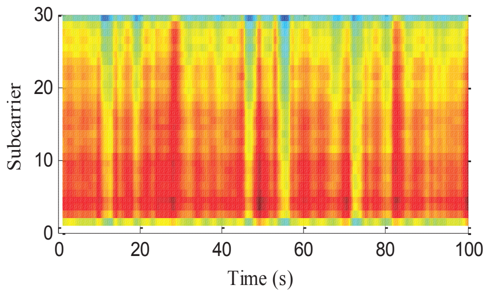


Figure 6 Walking signals over all subcarriers.

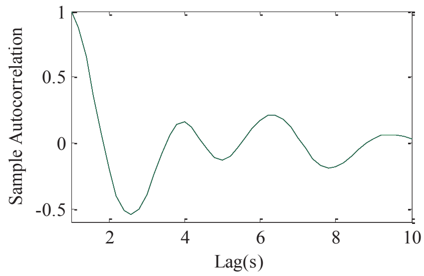


Figure 7 Autocorrelation of walking.

4.2 Measuring Gait Periodicity

CSI signals are sensitive to walking, yet amplitude responses are various in different subcarriers, see as Figure 6. So the individual subcarrier can not be used to analyze the gait periodicity. In this paper, first, CSI subcarriers are combined together by the weighted average method. The weighted average method can be written as:

$$CSI_{eff} = \frac{1}{K}\sum_{K=1}^{K}\frac{f_K}{f_0} \times |H_K|\,,\; K \in [1, 30] \tag{7}$$

Where f_0 is the center frequency; f_K is the K-th subcarrier frequency; $|H_K|$is the K-th subcarrier amplitude.

To obtain the gait periodicity from CSI, autocorrelation is used to analyze the periodicity due to it is a simple and powerful method to assess the periodic signals. It is easier to find the peaks in the autocorrelation of walking result in Figure 7. Each peak in autocorrelation means that the contour curve remains similar to the original version. The periodicity is analyzed by detecting the peaks in the autocorrelation function. The autocorrelation method can be written as:

$$\chi(m,n) = \frac{\sum_{k=0}^{k=n-1}\begin{bmatrix} CSI_{eff}(m+k) - \mu(m,n) \\ CSI_{eff}(m+k+n) - \mu(m+n,n)\end{bmatrix}}{n\sigma(m,n)\sigma(m+n,n)} \tag{8}$$

Where $\mu(k,n)$is mean of CSI sample sequence$\langle CSI_{eff}(k), CSI_{eff}(k+1), \cdots, CSI_{eff}(k+n+1)\rangle$; $\sigma(k,n)$ is the standard deviation of CSI sample sequence$\langle CSI_{eff}(k), CSI_{eff}(k+1), \cdots, CSI_{eff}(k+n+1)\rangle$.

4.3 Robustness of Gait Periodicity Analysis

In general, walking is a rhythm activity. Our study shows that performance of our method is not significantly affected by human gait. It is known that the position of human and the movement directions both can have an obvious influence on CSI amplitude [26]. Different people have different walking style. Furthermore, different people walking with different speeds and the sex, height, age, shape and size may have different influence on CSI. To study the robustness of our method against human gait, we collected samples from different people.

In Figure 8, we plot the autocorrelation results together with the CSI collected from laboratory to show the effectiveness of our periodicity analysis method. It performs autocorrelation for each activity of different people. We observe from this figure that gait periodicity of different people is obvious and it shows the robustness and stability of periodicity analysis (PA). And we also show impact of the target size on detection rate in the V section. In PA, we have no train phase to samples and we only use the feature of gait.

The above study shows that our method is robust to different speed. Different moving speeds also have different influence on CSI. CSI amplitude have a small change when human moving with a low speed. When target is moving fast, CSI may vary a lot in a short time. Robustness of different speeds analysis is shown in performance evaluation section. We compare with the basic method with different walking speed to show our method of PA has a better robustness.

5. PERFORMANCE EVALUATION

5.1 Experimental environments

In this section, we interpret the experiment setup and detailed performance evaluation of our method in various indoor scenarios.

In this paper, CISCO WRVS4400N wireless router is used as AP to transmitter data. Intel 5300 NICs is used as MP to receive data. In order to evaluate the extensible property of our method, experiments are performed in two typical indoor environments: laboratory and hall. The former is a typical NLOS indoor environment which covers an area of $7.4m \times 8.2m$ and is a rather complex multipath environment as shown in Figure 9(a). It has furniture and obstacles such as computers, tables and chairs. The latter is a typical LOS indoor environment which covers an area of approximately $6m \times 13.8m$ and is a rather sparse multipath environment as shown in Figure 9(b). There is a hall without any obstacles. The localization of AP and MP are as shown in Figure 9. The data are collected in two environments: static state and having a moving target in the environment.

To quantify the performance of our method, we focus on (1) True Positive rate (TP); (2) True Negative rate (TN); (3)

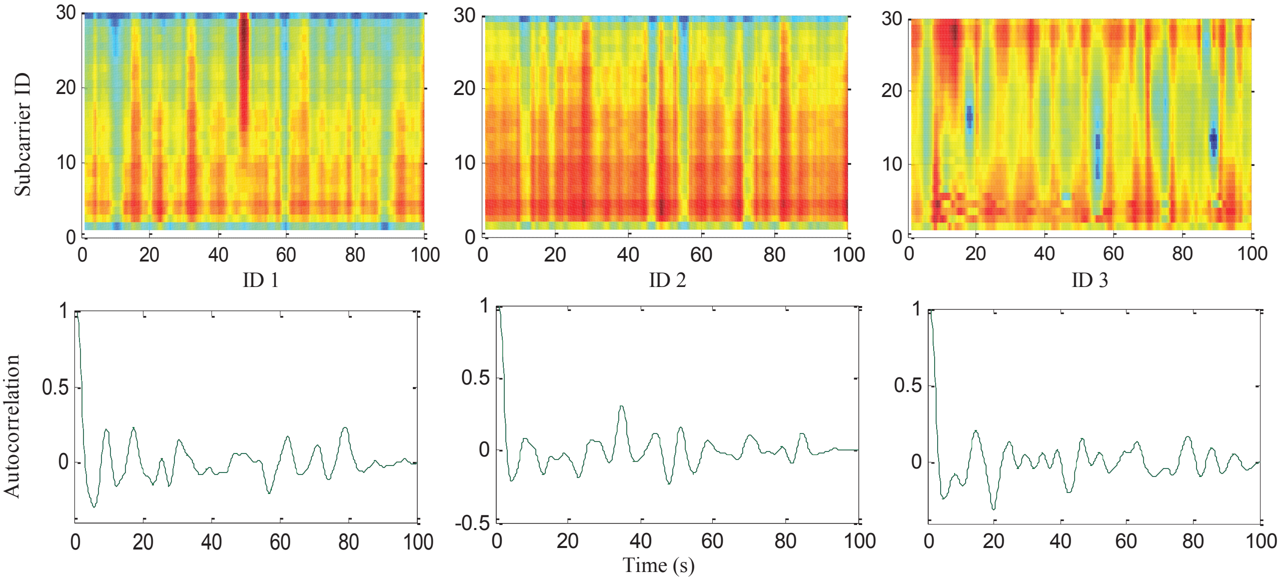
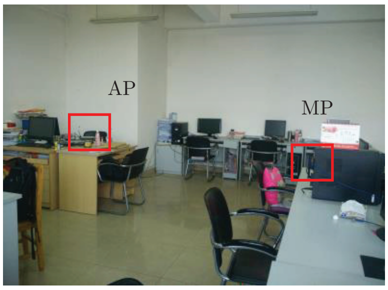
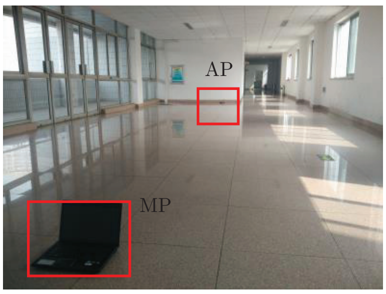


Figure 8 Robustness of gait periodicity analysis in different people.



(a) Laboratory



(b) Hall

Figure 9 Experimental environments.

False Positive rate (FP); (4) False Negative rate. In this paper, # presents there are moving targets; * presents there is no moving target. The meaning of each index as shown in table 1:

Table 1 The meaning of each index.

index	Detection results	Real results
TP	#	#
TN	*	*
FP	#	*
FN	*	#

The accuracy of our method can be shown as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100\% \tag{9}$$

The detection rate of our method can be shown as:

$$TPR = \frac{TP}{TP + FN} \times 100\% \tag{10}$$

$$TNR = \frac{TN}{TN + FP} \times 100\% \tag{11}$$

5.2 Performance

Our method has two phases. First is moving target detection phase. Second is gait periodicity analysis phase.

Overall detection accuracy. In this subsection, we answer the two following questions: First, what is the detection accuracy of this paper in different environments with different number of moving targets? Second, what is the detection rate in diverse scenarios? To answer the question we show the overall accuracy of moving targets detection in two typical indoor environments: our Lab (NLOS) and hall (LOS). Shown as Figure 10, all the results perform better in hall, due to the rather sparse multi-path environment. Compared with the results in laboratory, the method of this paper achieves high average accuracy of 94% in one target environment and 85% in three targets environment. Our method also achieves high TP and TN rates of 93.45% and 94% respectively, as shown in Figure 11.

Sample rate. To examine the impact of sample rate on the performance of PA, we increase the sample rate from 5 to 45. Figure 12 shows the moving target detection performance under different sample rate. The other conditions are the same. As can be seen in it, the results are not affected from the sample rate. This is because human moving activities affect the channel, and the features can be captured well.

Impact of sliding window size. With the growth of sliding window to a certain extent, the performance of detection gets better.

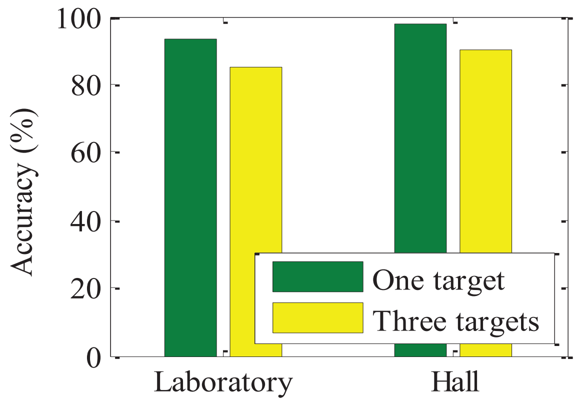


Figure 10 Accuracy in two environments when there are different moving targets.

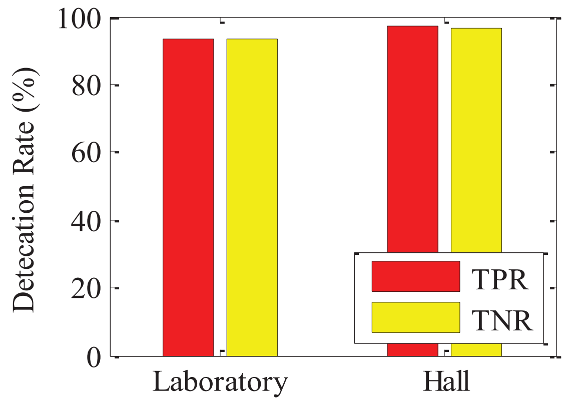


Figure 11 Detection rate in diverse scenarios.

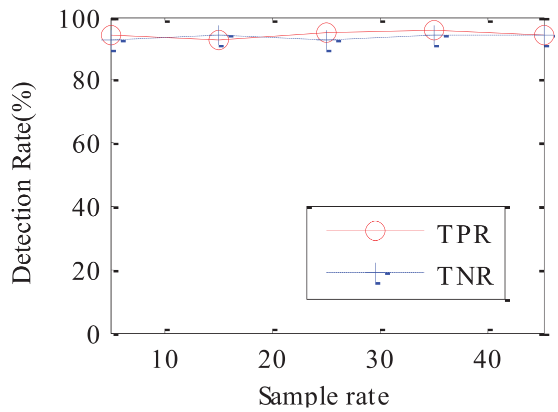


Figure 12 Impact of sample rate on detection accuracy.

Figure 13 shows the average detection rate with different sliding window when there is a slow walking in the lab. The sliding window the larger, the experimental results are more sensitive. On the other hand, if the sliding window is too small, it will be difficult to detect the existence of human. So it may reduce the detection rate and it make not easy to distinguish between static and dynamic environments. Compared with the other two systems, it is found that the detection rate increases with the growth of sliding window. But this trend is not immutable and frozen. The change causing by slow moving of CSI amplitude is relatively stable. When the sliding window size exceeds a certain threshold, the window is too large to detect it. And it may easy to cause large delay, make the detection rate rise trend reversal.

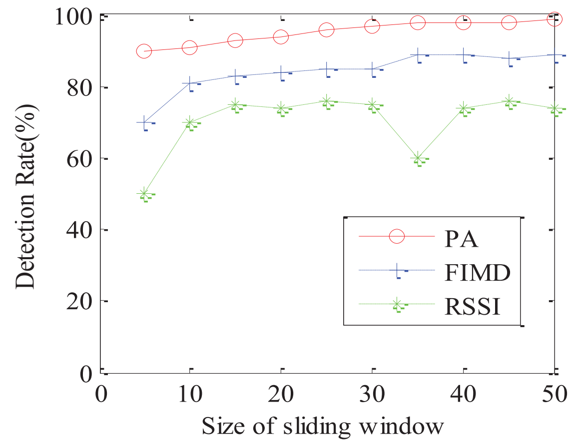


Figure 13 Impact of sliding window size.

Number of subcarriers. Compared with the single best subcarrier, the method of using all subcarriers has a better performance shown as Figure 14. It shows that using single subcarrier only provides a TP of 80% less than 13.45% when use all subcarriers. The reason behind this result is that subcarrier is sensitive to human activities, but it is dynamic change with the time.

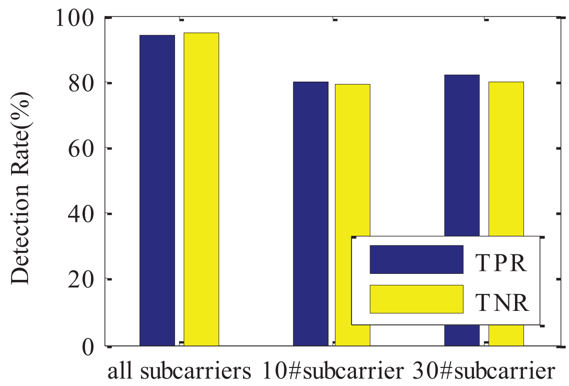


Figure 14 Impact of number of subcarriers on detection accuracy.

Number of CSI streams. Wireless signals travels in straight lines. The walls, equipment and moving targets will change the propagation path of wireless. The influence of human movement on different data streams is different due to different path of every pair of antennas. So multi data streams combined detection can improve the detection rate of the method in a certain extent. Figure 15 shows the detection performance under different number of CSI data streams. We can see from the result that the FN and FP have a downward trend with the increasing of data streams in a certain extent. The change of false positive rate and false negative rate is due to the different antennas with different multipath effect, and the received data packages in different pair of antenna are different. So in order to reduce the complexity of the algorithm and ensure the accuracy of detection, the best solution is 4 data streams.

Impact of different position. It is found that the performance of the system is the best when the human body is moving along

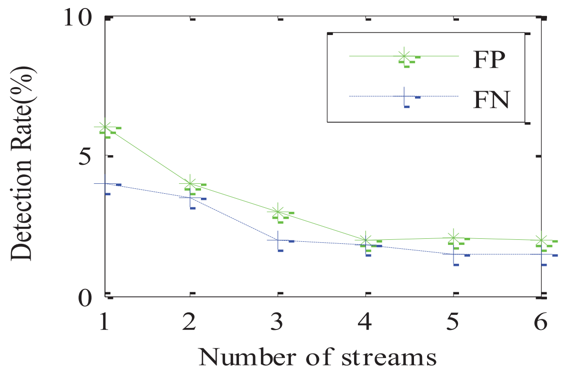


Figure 15 Impact of number of CSI data streams.

with the LOS of the transmitter and the receiver. With the AP-MP LOS propagation path as center, the detection rate decreases with the increase of the distance from the location of intruder to the AP-MP LOS path. The results are shown as Figure16. It can be seen that with the increase of the distance, the detection rate of the three kinds of detection systems is decreased. The reason behind this result is that the influence of CSI amplitude is obvious in LOS path. At the same time we can see that the performance of our method is better than the others. Because FIMD using the sliding window to filter outliers before fusing the data. When moving target slowly into interest area in the position farther away from AP-MP LOS path, the detection results are not obvious. The detection rate of RASID system is only about 20%. This is because RSSI is not stable. The RSS change caused by the human movement is hidden by its own changes.

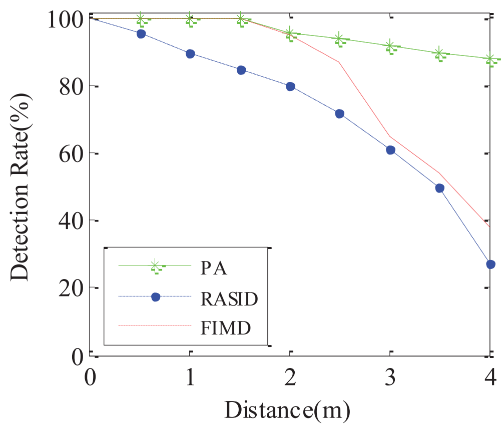


Figure 16 Impact of different distance.

Compare with the baseline methods. We compare the method of Periodicity Analysis (PA) with the baseline methods. See as Figure 17, it shows the performance of moving detection. As is shown, our method of PA achieves higher TPR and TNR than the amplitude variance methods and RSSI methods. This is because walking is a rhythm moving activity which can be separated from static state. RSSI has a very low resolution and a worse stability than CSI. Small changes in the environment will have a great impact on it and may cause a high false positive rate and false negative rate.

Impact of different speed of moving. Movement speed has a great influence on the performance of system. The faster the speed is, the greater the impact on CSI. When a target is walking fast, the CSI changes may vary a lot. Thus, CSI subcarrier feature may obvious in a sliding window. The speed has influence on gait period, but not walking periodicity. As shown in Figure 18, it shows the detection performance comparison of PA, FIMD and RASID when human into the interest area with different speed. The samples are divided into three types with different speed of 0.2∼0.6m/s, 0.6∼1m/s and1∼1.4m/s. System performances of FIMD and RASID have some decrease when people moving at a low speed. And CSI is more sensitive when human body is moving fast.

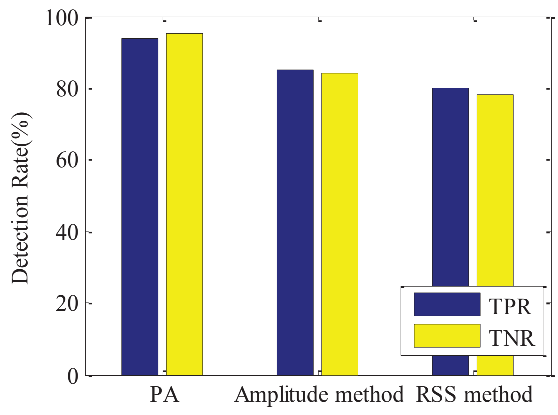


Figure 17 Detection rate using different methods.

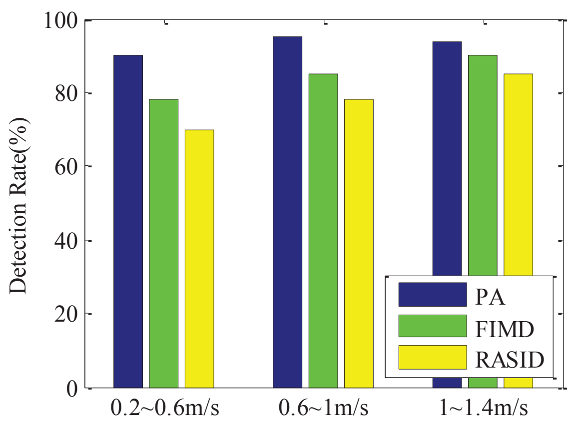


Figure 18 Detection rate with different speeds.

Impact of the target size. Different targets or people are of different sizes, e.g., height, weight and shape. We would like to study the impact of different target size on our method performance. Figure 19 illustrates the detection rate with six volunteers. ID 1 is a girl of 150 cm and 46 kg. ID 2 is a girl of 160 cm and 55 kg. ID 3 is a boy of 180 cm and 75 kg. ID 4 is a boy of 170 cm and 76 kg. ID 5 is an overweight boy of 170 cm and 85 kg. ID 6 is a child of 120 cm and 38 kg. The results show that the performance is well for different people with detection rate between 92% and 95% which do not vary much across different target size.

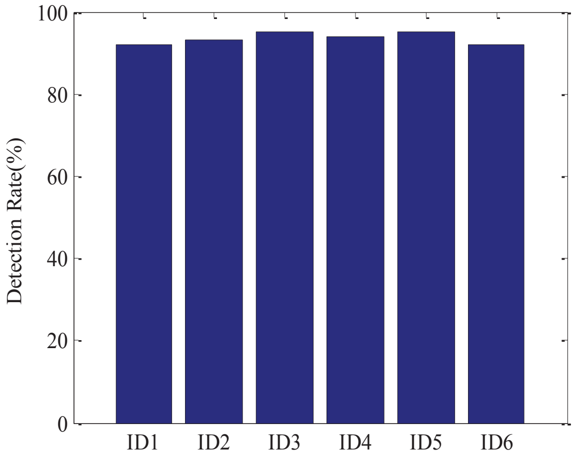


Figure 19 Impact of different target size.

6. CONCLUSION

This paper presents that CSI is sensitive to human activities and the sensitivity can be used for detecting moving targets in the environments and recognizing human activities. We propose a PCA and DWT based multi-layer filtering framework to serve for detecting features of CSI subcarriers. Taking advantage of the feature difference and correlation detected from CSI subcarriers, the proposed approach leverages the CSI streams to analyze the gait periodicity of human walking. As a result, the higher robustness of moving targets detection has been achieved in different scenes.

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REFERENCES

1. Aggarwal J K, Ryoo M S. Human activity analysis: A review [J]. ACM Computing Surveys (CSUR), 2011, 43(3): 16.
2. Wu, C., Yang, Z., Zhou, Z., Liu, X., Liu, Y., and Cao, J. Non-invasive detection of moving and stationary human with wifi[J]. IEEE Journal on Selected Areas in Communications, 2015, 33(11): 2329-2342.
3. Wang, W., Liu, A. X., Shahzad, M., Ling, K., and Lu, S. Understanding and modeling of wifi signal based human activity recognition[C]//Proceedings of the 21st Annual International Conference on Mobile Computing and Networking. ACM, 2015: 65-76.
4. Han, C., Wu, K., Wang, Y., and Ni, L. M. WiFall: Device-free fall detection by wireless networks[C]//IEEE INFOCOM 2014-IEEE Conference on Computer Communications. IEEE, 2014: 271-279.
5. Luhandjula, T., Djouani, K., Hamam, Y., van Wyk, B. J., and Williams, Q. A visual hand motion detection algorithm for wheelchair motion [M]//Human–Computer Systems Interaction: Backgrounds and Applications 2. Springer Berlin Heidelberg, 2012: 433-452.
6. Rangarajan, S., Kidane, A., Qian, G., Rajko, S., and Birchfield, D. The design of a pressure sensing floor for movement-based human computer interaction [M]// Smart sensing and context. Springer Berlin Heidelberg, 2007: 46-61.
7. Yang, J., Ge, Y., Xiong, H., Chen, Y., and Liu, H. Performing joint learning for passive intrusion detection in pervasive wireless environments [C]// INFOCOM, 2010 Proceedings IEEE. IEEE, 2010: 1-9.
8. Kosba, A. E., Saeed, A., and Youssef, M.. Rasid: A robust wlan device-free passive motion detection system [C]//Pervasive computing and communications (PerCom), 2012 IEEE international conference on. IEEE, 2012: 180-189.
9. Zhang, D., Liu, Y., Guo, X., and Ni, L. M. Rass: A real-time, accurate, and scalable system for tracking transceiver-free objects [J]. Parallel and Distributed Systems, IEEE Transactions on, 2013, 24(5): 996-1008.
10. Yang Zheng, Liu Yun-hao. Wifi Radar:From RSSI to CSI. [J] China Computer Association Newsletter. 2014, 11(10):55-59.
11. Pu, Q., Gupta, S., Gollakota, S., and Patel, S. Whole-home gesture recognition using wireless signals[C]//Proceedings of the 19th annual international conference on Mobile computing & networking. ACM, 2013: 27-38.
12. Wang, G., Zou, Y., Zhou, Z., Wu, K., and Ni, L. M. We can hear you with wi-fi![C]//Proceedings of the 20th annual international conference on Mobile computing and networking. ACM, 2014: 593-604.
13. Kellogg B, Talla V, Gollakota S. Bringing gesture recognition to all devices[C]//11th USENIX Symposium on Networked Systems Design and Implementation (NSDI 14). 2014: 303-316.
14. Ralston T S, Charvat G L, Peabody J E. Real-time through-wall imaging using an ultrawideband multiple-input multiple-output (MIMO) phased array radar system[C]//Phased Array Systems and Technology (ARRAY), 2010 IEEE International Symposium on. IEEE, 2010: 551-558.
15. Zhu, F., Gao, S., Ho, A. T. S., Brown, T. W., Li, J., and Xu, J. D. Low-profile directional ultra-wideband antenna for see-through-wall imaging applications[J]. Progress In Electromagnetics Research, 2011, 121: 121-139.
16. Levanon N, Mozeson E. Radar signals[M]. John Wiley & Sons, 2004.
17. Zheng, X., Wang, J., Shangguan, L., Zhou, Z., and Liu, Y. Smokey: Ubiquitous smoking detection with commercial wifi infrastructures[C]//IEEE INFOCOM 2016-The 35th Annual IEEE International Conference on Computer Communications. IEEE, 2016: 1-9.
18. Zhou, Z., Yang, Z., Wu, C., Shangguan, L., and Liu, Y. (2013). Towards omnidirectional passive human detection. [J] In INFOCOM, 2013 Proceedings IEEE (pp. 3057–3065).
19. Qian, K., Wu, C., Yang, Z., Liu, Y., and Zhou, Z. PADS: passive detection of moving targets with dynamic speed using PHY layer information[C]//Parallel and Distributed Systems (ICPADS), 2014 20th IEEE International Conference on. IEEE, 2014: 1-8.
20. Abdelnasser H, Youssef M, Harras K A. Wigest: A ubiquitous wifi-based gesture recognition system[C]//2015 IEEE Conference on Computer Communications (INFOCOM). IEEE, 2015: 1472-1480.
21. Abdel-Nasser, H., Samir, R., Sabek, I., and Youssef, M. Mono-

PHY: Mono-Stream-based Device-free WLAN Localization via Physical Layer Information. [J]//Wireless Communications and Networking Conference(WCNC).2013.
22. I Sabek, M Youssef. MonoStream: A Minimal-Hardware High Accuracy Device-free WLAN Localization System. [J]//arXiv:1308.0768.
23. Patwari N, Kasera S K. Robust location distinction using temporal link signatures[C]//Proceedings of the 13th annual ACM international conference on Mobile computing and networking. ACM, 2007: 111-122.
24. Vasisht D, Kumar S, Katabi D. Decimeter-level localization with a single WiFi access point[C]//13th USENIX Symposium on Networked Systems Design and Implementation (NSDI 16). 2016: 165-178.
25. Zhou, Z., Yang, Z., Wu, C., Sun, W., and Liu, Y. Lifi: Line-of-sight identification with wifi. [C]//INFOCOM, 2014 Proceedings IEEE. IEEE, 2014: 2688-2696.
26. Willis N J. Bistatic radar[M]. SciTech Publishing, 2005.