Robust and Passive Motion Detection with COTS WiFi Devices

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Abstract: Device-free Passive (DfP) detection has received increasing attention for its ability to support various pervasive applications. Instead of relying on variable Received Signal Strength (RSS), most recent studies rely on finer-grained Channel State Information (CSI). However, existing methods have some limitations, in that they are effective only in the Line-Of-Sight (LOS) or for more than one moving individual. In this paper, we analyze the human motion effect on CSI and propose a novel scheme for Robust Passive Motion Detection (R-PMD). Since traditional low-pass filtering has a number of limitations with respect to data denoising, we adopt a novel Principal Component Analysis (PCA)-based filtering technique to capture the representative signals of human motion and extract the variance profile as the sensitive metric for human detection. In addition, existing schemes simply aggregate CSI values over all the antennas in MIMO systems. Instead, we investigate the sensing quality of each antenna and aggregate the best combination of antennas to achieve more accurate and robust detection. The R-PMD prototype uses off-the-shelf WiFi devices and the experimental results demonstrate that R-PMD achieves an average detection rate of 96.33% with a false alarm rate of 3.67%.

Key words: device-free passive detection; Received Signal Strength (RSS); channel state information; MIMO

1 Introduction
The ubiquitously deployed wireless indoor networks have fostered myriad mobile and computing applications, which serve as more than communication vehicles. Fast-emerging applications, such as indoor localization, device-free passive detection, and activity recognition, continue to revolutionize the industry[1].

Device-free Passive (DfP)[2,3] detection is an emerging technology for detecting whether there are any entities moving around areas of interest without the need to attach any device to them. DfP detection is a key enabler for a broad range of applications, including intrusion detection for safety precautions, identification of trapped people in fire or earthquake situations, and border detection[4], to name a few. In such applications, traditional device-based techniques that require specialized hardware like accelerometers and pressure sensors are no longer applicable. Therefore, DfP detection is drawing growing interest.

With the advent of wireless communications, there has been a worldwide convergence of Wireless Local Area Networks (WLANs) that provide low cost and open access, and which also provide an opportunity for the use of DfP detection alongside the well-established WLAN infrastructure. Many researchers[5–7] have adopted Received Signal Strength (RSS) as the base modality for DfP detection due to its handy accessibility with commodity devices. These RSS-based DfP detection systems leverage the variations of RSS measurements to capture anomalous environmental
changes that occur when an intruder enters the area of interest. Although previous RSS-based techniques have made great progress, they continue to suffer from RSS’s coarse granularity and high susceptibility. Specifically, the high temporal variability of RSS measurements makes it less sensitive to human motion-induced environmental changes, resulting in unsatisfactory human detection accuracy.

Fortunately, there is a way to virtually tune the above situation. In the currently widely used Orthogonal Frequency-Division Multiplexing (OFDM) systems, where data are modulated on multiple subcarriers at different frequencies and transmitted simultaneously, there is a notation called Channel State Information (CSI) from the physical layer, which estimates the channel property over each subcarrier. Compared to RSS, CSI, which is now tractable on commodity Network Interface Cards (NICs), is finer-grained PHY-layer information that describes the amplitude and phase on each subcarrier in the frequency domain. CSI has proved to be a more robust and reliable metric for two reasons. First, CSI has anti-interference capacity in the 2.4-GHz band, thanks to its frequency diversity property. Second, CSI is independent of Access Point (AP) power adjustment, unlike the susceptible RSS, and it remains fairly stable in static environments while also being quite sensitive to human motion. These factors make CSI a promising metric for DfP detection systems. In Refs. [11, 12], the authors utilized a CSI-based correlation matrix and estimated human motion based on the eigenvalue distribution of the correlation matrix. However, in our preliminary experiments, we observed that this approach has some limitations regarding the walking area and the number of walking people, i.e., these systems are sensitive only when people are near the AP and Detection Point (DP) or when there is more than one moving individual, thus leading to serious mis-detection. In Ref. [13], the authors exploited the CSI fingerprint for omnidirectional human detection. However, the CSI fingerprint can become quite random in dynamic scenarios, resulting in poor detection accuracy.

In this paper, we propose a novel metric from the CSI to overcome the above limitations of DfP detection. We present a design for a Robust Passive Motion Detection (R-PMD) system that achieves better detection performance. With this design, we first measure and collect CSI samples with Commercial Off-The-Shelf (COTS) NICs from DPs fixed in the area of interest. Then, we apply the data preprocessing module to filter out outliers and eliminate data noise to derive useful signals. Next, we adopt a variance-based approach to extract the feature profile from the filtered CSI data with respect to different environmental states, i.e., static and moving human presences. To classify the obtained feature pattern, we adopt a threshold-based method to infer the environmental state. Finally, to improve the detection precision and robustness, we exploit and integrate CSIs over multi-antennas in MIMO systems.

Based on our previous work in Ref. [14], we improve the performance of DfP detection by adopting a novel Principal Component Analysis (PCA)-based CSI filtering technique and considering different combinations of antennas. Our main contributions are summarized as follows.

- We investigate the performance and identify the limitations of the well-known CSI-based system FIMD under different conditions, including different walking areas and a different number of walking entities.
- We analyze the limitations of traditional low-pass filtering in data denoising and adopt a novel PCA-based filtering technique to capture the representative signals of human motion and extract the variance profile as the sensitive metric for target detection, thereby improving both the denoising performance and system efficiency.
- We utilize the space diversity provided by multi-antennas in modern MIMO communication systems by investigating the quality of each antenna and choosing the best combination of antennas for more accurate and robust detection.
- We develop a prototype R-PMD using COTS WiFi devices and evaluate it in a typical indoor scenario, i.e., a multipath-rich laboratory. Experimental results demonstrate that R-PMD can achieve a true positive rate of 96.33% for moving people with a false alarm rate of 3.67%, far above the CSI-based FIMD system performance.

The rest of this paper is organized as follows. First, we review related work in Section 2, followed by some preliminaries in Section 3, including a brief background about CSI and MIMO, and the property that can be used to identify human motion. In Section 4, we give an overview of the system architecture and we present the design details in Section 5. Then, in Section 6, we describe the implementation and experimental results of
R-PMD. We discuss its limitations and our plans for future work in Section 7 and draw our conclusions in Section 8.

2 Related Work

Due to its wide application potential, motion detection has become an active area of research with respect to intrusion detection, smart homes, traffic estimation, and other areas. Due to the rapid development of wireless techniques, researchers recently proposed the concept of DfP detection\(^2\), which is garnering increasing attention. There are two primary categories of techniques related to DfP detection: RSS-based detection and CSI-based detection. Below, we describe representative work related to these techniques.

**RSS-based detection.** RSS is especially attractive for DfP detection due to its handy accessibility with commodity devices. Existing RSS-based detection schemes usually correlate the variations of RSS with the environmental changes caused by human locomotion. More specifically, a large RSS variance value indicates a moving target in the monitoring area whereas a small value infers none. Youssef et al.\(^2\) discussed the challenges of DfP techniques and proposed both moving average and moving variance-based feature extraction algorithms for motion detection. Moussa and Youssef\(^3\) proposed a maximum likelihood estimator-based algorithm to improve the performance of DfP systems in a real environment. Yang et al.\(^7\) proposed a joint intrusion learning approach, which has the ability to combine the detection power of several complementary intrusion indicators and simultaneously detect different intrusion patterns. To compensate for RSS’s unreliability, Wilson and Patwari\(^16\) proposed Radio Tomographic Imaging (RTI), which deploys a sensor network around the target area and embraces the redundancy introduced by the dense-deployed sensors to visualize human-induced RSS attenuations. An extension of the RTI technique, VRTI, was proposed in Ref. \(^17\), which takes advantage of the motion-induced variance of RSS measurements. Another RSS-based system, RASID\(^5\), improves detection accuracy by analyzing the RSS features and adopting a nonparametric technique that adapts to environmental changes.

**CSI-based detection.** Since CSI can be exported from commodity wireless NICs\(^9\), many researchers have resorted to finer-grained CSI to realize better detection. Similar to RSS-based schemes, most CSI-based approaches also leverage variations of CSI measurements to infer the presence of moving entities. FIMD\(^11\) leverages the eigenvalues of a CSI-based correlation matrix in a given period to enable accurate fine-grained burst motion detection. Pilot\(^12\) is an early attempt in device-free positioning, which exploits the correlation of CSI over time to monitor abnormal appearances and to locate the target. Omni-PHD\(^13\) uses omnidirectional sensing coverage for DfP detection, and exploits the multipath components captured by CSI. PADS\(^18\) exploits the full information (both amplitude and phase) provided by CSI to accurately detect walking humans with dynamic speeds, based on the eigenvalues of a covariance matrix of normalized CSI. WiFall\(^19\) adopts a local outlier factor-based anomaly detection algorithm to detect human motion and isolates the corresponding anomaly patterns for further activity classification. DeMan\(^20\) extracts the maximum eigenvalues of the correlation matrices of successive activity classification. In this paper, we adopt a novel PCA-based filtering technique to capture the representative signals of human motion and to extract the variance profile as the sensitive metric for target detection regardless of different conditions. We also analyze the quality of different antennas and improve detection performance by selecting the best combination of antennas.

3 Preliminaries

In this section, we briefly introduce necessary background information regarding the CSI and MIMO technology we use, along with the basic principle upon which our system is based.

3.1 CSI

OFDM is a bandwidth-efficient digital multicarrier modulation scheme for high-data-rate wireless
communications and has been endorsed in leading industry standards, including IEEE 802.11 a/g/n, WiMAX, and LTE. In OFDM, signals are transmitted over multiple orthogonal frequencies called subcarriers and each subcarrier-transmitted signal has a different signal and phase. While RSS is the most accessible proxy of channel conditions, it is only a coarse amplitude estimation for a wireless channel, regardless of the number of antennas or subcarriers.

Recently, some of the common IEEE 802.11n standard-based NICs available on the market, e.g., the Intel 5300 card, can provide detailed magnitude and phase information about the different subcarriers represented as CSI. Specifically, by leveraging an off-the-shelf Intel 5300 NIC with a slight driver modification, a sampled version of the Channel Frequency Response (CFR) within the WiFi bandwidth on $N = 30$ subcarriers can be revealed to upper layers in the CSI format\[9\]:

$$H_D = [H(f_1), H(f_2), \ldots, H(f_i), \ldots, H(f_i)]^T, i \in [1, N]$$ \hspace{1cm} (1)

where each CSI $H(f_i)$ depicts the amplitude and phase of an OFDM subcarrier:

$$H(f_i) = ||H(f_i)||e^{j\sin \angle H(f_i)}$$ \hspace{1cm} (2)

where $H(f_i)$ is the CSI for the subcarrier with a central frequency of $f_i$, and $\angle H(f_i)$ denotes its phase. Compared with RSS, CSI depicts finer-grained temporal and spectral structures of wireless links with respect to both amplitude and phase.

### 3.2 MIMO technology

With the advent of the information age, spectrum resources have become scarcer. The key feature of 802.11n equipment that sets it apart from earlier 802.11 a/g equipment is the use of multiple antennas on which the MIMO techniques are based\[21\]. MIMO technology uses multiple antennas\[22\] to improve data throughput and transmission distance without enhancing the bandwidth or total transmission power. In MIMO, there are multiple transmitters and receiver antennas, and each combination of receiver and transmitter antennas function as a separate transmit-receive (TX-RX) stream. So, the CSI for all the TX-RX streams can be expressed as follows:

$$\text{CSI}_\text{MIMO} = \begin{bmatrix} H_{11} & H_{12} & \cdots & H_{1M} \\ H_{21} & H_{22} & \cdots & H_{2M} \\ \vdots & \vdots & \ddots & \vdots \\ H_{N1} & H_{N2} & \cdots & H_{NM} \end{bmatrix}$$ \hspace{1cm} (3)

where $M$ and $N$ are the number of transmitter and receiver antennas, respectively, and $H_{NM}$ is the CSI of the $M$-th antenna of the transmitter sent to the $N$-th antenna of the receiver. Since each TX-RX stream takes different paths in the indoor environment, the $H_{NM}$ is distinct, which results in distinctive CSIs received at different antennas.

### 3.3 CSI property

In this section, we show the CSI property that can be used to detect moving entities. To demonstrate the impact of moving entities, we perform some controlled experiments. Figure 1 depicts the CSI amplitude of a TX-RX stream for 100 packets in different environments, i.e., a static environment and an individual walking in both LOS and Non-Line-Of-Sight (NLOS) areas. Regardless of an individual’s walking area, the CSI amplitude is obviously more dispersed in a dynamic environment than in a static environment, demonstrating that the CSI amplitude can be used to identify human appearance.

### 4 Overview

In this section, we describe the overall architecture of R-PMD, as illustrated in Fig. 2. During the CSI

![Fig. 1 CSI amplitude of a TX-RX stream for 100 packets in different environments: (a) static environment; (b) one individual walking in LOS area; and (c) one individual walking in NLOS area.](image-url)
collection phase, we measured and collected CSIs from commodity WiFi devices using an off-the-shelf NIC, i.e., Intel 5300.

An efficient and robust detection system has three main functional components: data preprocessing, feature extraction, and anomaly detection. First, CSIs are exported from the commodity NIC, which receives packets from an ordinary wireless router. Since the imported raw CSI measurements could contain outliers and noise, we pass the CSI sequence through the data preprocessing module first for outlier removal, interpolation, low-pass filtering, and PCA-based filtering. Then, the processed data are fed to the feature extraction module, which is the most critical part of our system. In R-PMD, the feature extraction module estimates the variance distribution of the filtered CSI sequence in two phases: the offline training phase and the online monitoring phase. During the offline training phase, there is no need to construct fingerprints of every point. Instead, we collect CSIs when the environment has no one in it for one minute and apply the feature extraction module to simply and easily obtain the static fingerprint. During the online monitoring phase, the anomaly detection module constructs the variance distribution profile using the feature extraction module and decides whether there is any human motion by comparing the static and online profiles. Specifically, we use the Earth Mover’s Distance (EMD) algorithm [23] to infer the degree of abnormality. Also, to enhance the accuracy and robustness of our system, we examine and integrate multiple antennas used in modern MIMO systems. Finally, based on the results of the anomaly detection module, an alarm is or is not released.

5 Methodology

In this section, we detail the measurements used in the design of R-PMD. As illustrated above, CSI contains both amplitude and phase information. To compare the stabilities of the amplitude and phase, Fig. 3 shows the amplitude and phase of 100 packets in a static environment. We can see that the amplitude maintains good stability in the presence of some noise while the phase performs quite randomly even in a static environment. Although we can mitigate phase randomness to a great extent, as in Refs. [18, 20], Intel 5300 NIC is known to have a firmware issue on the 2.4-GHz bands and is only able to obtain reliable phase readings at 5 GHz [24]. Since we adopted the Intel 5300 NIC at 2.4 GHz in our experiments, here we focus on the CSI amplitude and leave the leveraging of phase information for future work.

5.1 CSI data preprocessing

Prior to monitoring an area of interest, CSIs must first be processed for better detection.

5.1.1 Outlier removal and interpolation

The first step in processing a CSI sequence is to remove outliers [25]. We found there to be some abrupt changes in CSI amplitudes in the collected CSI sequences, which had obviously not been caused by human motion. These outliers might appear in CSI measurements due to protocol specifications or environmental noises [18]. As our approach involves variation-based detection, these outliers can greatly affect the detection performance and must be sifted out.

To identify and remove these biased measurements, we utilize a Hampel identifier [26], which identifies as an outlier any point that falls outside the closed interval...
\[ \mu - \gamma \sigma, \mu + \gamma \sigma \], where \( \mu \) and \( \sigma \) are the median and the Median Absolute Deviation (MAD) of the data sequence, respectively. \( \gamma \) is an application dependent parameter and the most widely used value is 3. In addition, to account for the CSI information removed by the Hampel identifier, we apply the 1-D linear interpolation algorithm in MATLAB to obtain equally spaced samples. Figure 4 shows the original CSI and the CSI after outlier removal and interpolation in a static environment. We can see that there are some outliers in Fig. 4a, which have been effectively removed in Fig. 4b by the Hampel identifier and interpolation.

### 5.1.2 Low-pass filtering

The CSI data exported by COTS NICs are inherently noisy due to the complex indoor environment, which includes such factors as electromagnetic interference, air pressure, and temperature changes. To use CSI values for DfP detection, this noise must be eliminated. To do so, R-PMD first passes the CSI sequences through a low-pass filter to remove high-frequency noises after outlier removal and interpolation. Specifically, we reduce the environmental noise by employing the Weighted Moving Average (WMA) technique. In a CSI sequence, such as \( \text{CSI}_1, \text{CSI}_2, \cdots, \text{CSI}_t \), we average the CSI value at time \( t \) by the previous \( m \) values. The latest CSI has weight \( m \), the second latest \( m - 1 \), and so on to one:

\[
\text{CSI}_t = \frac{1}{m + (m-1) + \cdots + 1} \times (m \times \text{CSI}_t + (m-1) \times \\
\quad \text{CSI}_{t-1} + \cdots + 1 \times \text{CSI}_{t-m+1})
\]

(4)

where \( \text{CSI}_t \) is the averaged new CSI. The value of \( m \) decides to what degree the current value is related to historical records. As an illustration, Fig. 5 shows all 30 CSI sequences before and after WMA filtering. We can clearly see that the original noisy CSI signals become much cleaner following the removal of most of the burst noises.

### 5.1.3 PCA-based filtering

In contrast to the direct feature extraction from each subcarrier performed in Ref. [14], in this study, we applied PCA on the primary denoised CSI sequence to extract more representative signals. Specifically, we let \( \mathbf{H}_i \) be the \( 30 \times 1 \) dimensional vector which contains the WMA-filtered CSI values for the \( i \)-th packet and \( \mathbf{F} \) is a \( K \times 30 \) dimensional matrix representing the CSI values for \( K \) consecutive packets. Then, we can express the CSI sequences as follows:

\[
\mathbf{F} = [\mathbf{H}_1, \mathbf{H}_2, \ldots, \mathbf{H}_K]^T
\]

(5)

The columns of the matrix \( \mathbf{F} \) denote the CSI sequences for each subcarrier. R-PMD calculates the principal components \( \mathbf{P} \) as follows:

\[
\mathbf{P} = (P_1, P_2, \ldots, P_i), i \in [1, 30]
\]

(6)
where $P_i$ is the $i$-th principal component. Figure 6 shows the plot of the top five principal components in both the static and dynamic environments. Unfortunately, as shown in the figure, the constructed first principal component fluctuates severely regardless of the presence of a moving human, although the others display higher variations in the presence of a moving human, which indicates that the low-pass filtering component alone is insufficient for noise removal. In fact, although low-pass filtering has eliminated most of the burst noises, some noises remain due to the internal state changes in the WiFi devices, including transmission power changes, transmission rate adaptation, and internal CSI reference level changes\cite{27, 28}.

To further sanitize the still distorted CSI, we leverage the correlated variations among the different CSI subcarriers and adopt a novel PCA-based filtering component to obtain clean CSI for feature extraction. Figure 7 shows the variance of CSI over different subcarriers for one TX-RX stream both in the presence and absence of a moving human. From this figure, we can see that although they differ in absolute value, the different subcarriers show correlated variations under the influence of human motion. Based on this observation, we discard the noisy first principal component and retain the remaining ones for feature extraction. Thanks to the correlated variations of the different subcarriers, the removal of the first principal component does not lead to any significant information loss since the remaining principal components contain enough information to successfully detect human motion, whereas the uncorrelated noise components are mainly in the first principal component.

5.2 Feature extraction

Feature extraction is a prerequisite of the following work. Therefore, we first analyze the limitations of FIMD\cite{11}, which is a well-known eigenvalue-based method. Then, we propose our variance-based scheme to model the CSI amplitude feature.

5.2.1 Analysis of FIMD

In order to analyze the performance of FIMD under different conditions, we performed some controlled experiments. We programed the AP to transmit 100 packets per second and measured the CSIs for each testing case for about 30 seconds, from which we selected the CSIs of the first 1000 packets as one test sample. We collected samples including only one moving individual and with three moving individuals in both LOS and NLOS areas. Figure 8 shows the eigenvalue distributions for the different scenarios. A comparison of the experimental results reveals that FIMD is effective only when people walk in the LOS area or there is more than one moving individual. We verify the drawbacks of FIMD in the evaluation section.

5.2.2 Modeling the CSI amplitude feature

Since the eigenvalue-based method has some
limitations, as determined above, we adopt a variance-based scheme to differentiate the CSI dynamic pattern from the stationary pattern based on the movement of entities. Specifically, we process continuous CSIs over different sliding windows. Let $Z$ be the filtered CSI sequence over a specific sliding window $W$ with length $l$. Then, the filtered CSI sequence is an $l \times 1$ matrix and can be expressed as

$$Z = \begin{bmatrix} Z_1, Z_2, \ldots, Z_l \end{bmatrix}^T$$ (7)

Then, the variance over $l$ sequential packets is given by the following:

$$\text{Var}(Z) = \frac{1}{l} \sum_{i=1}^{l} \left( Z_i - \frac{1}{l} \sum_{j=1}^{l} Z_j \right)^2$$ (8)

We can then obtain a single value from the equation above. With the sliding window moving $m$ times, we obtain a $1 \times m$ matrix $T$. In our previous work[14], we calculated the variances for 30 filtered CSI sequences and obtained a $30 \times m$ matrix, in which each row represented the variance of a subcarrier. Figure 9 shows the probability distribution histograms of CSI variance of the first subcarrier corresponding to Fig. 8 without performing PCA-based filtering.

In this paper, since we perform PCA-based filtering on CSI and discard the first principal component, we calculate the variance of the remaining principal components. Considering PCA ranks principal components in descending order of their variances, we need not calculate the variance of all the principal components. The number of principal components used for feature extraction represents a tradeoff between classification performance and computational complexity. We chose two principal components, i.e., $P_2$ and $P_3$, in our implementation, which have been shown in our experiments to contain enough significant variations caused by human motion. Figure 10 depicts the probability distribution histograms of CSI variance for the second principal component corresponding to Fig. 8. As illustrated in Figs. 9 and 10, we can see that most of the variance values concentrate around 0 in the static environment whereas the values tend to rise and disperse in the presence of moving entities in both LOS and NLOS areas.

5.3 Motion detection

We collected CSI measurements with no one in the vicinity for just one minute and stored its histogram as a static fingerprint in the offline phase. By comparing the histograms obtained in the online phase with the static one, we can determine whether there is someone moving. To compare the similarity between two variance histograms, we use the EMD algorithm[23]. EMD is a similarity metric for calculating the distance between two histograms, which is
analogous to the minimal effort required to transport one pile of earth to another. In general, the EMD calculates the dissimilarity between two signatures $P = \{(p_i, u_i)\}_{i=1}^{m}$ and $Q = \{(q_j, v_j)\}_{j=1}^{n}$, where $u_i$ and $v_j$ represent the positions of the $i$-th and $j$-th elements in each signature, and $p_i$ and $q_j$ denote the corresponding weights, respectively. The EMD between $P$ and $Q$ is then given by the following:

$$\text{EMD}(P, Q) = \min_{F=\{f_{ij}\}} \frac{\sum_{i,j} f_{ij}d_{ij}}{\sum_{i,j} f_{ij}}$$

(9)
with the following constraints:

\[ \sum_j f_{ij} \leq p_i, \sum_i f_{ij} \leq q_j, \]
\[ \sum_i f_{ij} = \min(\sum_i p_i, \sum_j q_j), f_{ij} \geq 0. \]

In this paper, \( P \) and \( Q \) denote the histogram in the offline and online phases, respectively, where \( u_i \) and \( p_i \) are the corresponding position and probability of the \( i \)-th histogram bin, respectively.

As illustrated in Fig. 7, although the variances over different subcarriers differ in absolute value, they all become dispersed under the influence of human motion. In our previous work\(^{[14]} \), we had therefore calculated the EMD for each subcarrier before adding the \( N = 30 \) EMDs into a single distance \( \phi \) to obtain the overall dissimilarity, in which the size reflects the degree to which the environment is abnormal. In this paper, since we select only the second and third principal components for DfP detection, we simply aggregate the EMDs for \( P_2 \) and \( P_3 \) as the final distance \( \phi \), which greatly reduces the computational complexity of our system. Then, we compare \( \phi \) with a pre-determined threshold \( \alpha \). If \( \phi \) is greater than \( \alpha \), this indicates that there is someone moving in the monitored area. Otherwise, the environment is deemed to be static.

### 5.4 Multi-antennas enhancement

The use of multiple antennas at the receiver and transmitter has revolutionized wireless communications over the past decade. It has long been known that multiple receive antennas can improve reception through the selection of a stronger signal or a combination of individual signals at a receiver\(^{[21]} \). Adding multiple antennas to an 802.11n receiver or transmitter provides a new set of independently faded paths, even if the antennas are separated by only a few centimeters. This adds spatial diversity to the system, which can be used to improve sensitivity.

Since COTS wireless devices are commonly equipped with multiple antennas, we also use multiple antennas to improve the precision and robustness of our system. However, existing systems with multiple antennas simply aggregate the CSI values of all the antennas without considering the sensing quality of each antenna. As illustrated in Fig. 11, the amplitude varies in three antennas of the same testing case and fluctuate more obviously on antennas B and C, which indicates that the impact of human motion on each antenna is distinct. In fact, antenna A performs poorly with the worst detection rate and the use of a “bad” antenna will cause performance degradation, as we demonstrate in our experiments. Taking the sensing quality of different antennas into consideration, we test the detection performance for different antenna combinations, calculate the median distance of the combined antennas for detection, and select the best antenna combination for human detection, which we demonstrated in our experiments to be a simple and effective process.

### 6 Performance Evaluation

In this section, we describe our implementation and experimental evaluation of R-PMD. First, we describe our test bed and data collection methodology. Then, we analyze the effect of antenna combination, window size, and number of principal components on system performance, along with the overall DfP detection performance. Lastly, we comprehensively compare R-PMD with the CSI-based system FIMD.

#### 6.1 Experimental methodology

In the evaluation, we employed a single antenna TP-LINK TL-WR742N wireless router as the transmitter and a mini PC equipped with Intel 5300 NICs as the receiver pinging packets from the AP. The mini PC was equipped with three external antennas, as shown in Fig. 12a, which created a \( 1 \times 3 \) MIMO system. The transmission rate was 100 packets per second. We describe in detail the experimental settings in the following.

We conducted our experiments in an \( 8.5 \times 11 \) m research laboratory on our campus, which is piled with desks and computers, thus creating a rather complex multipath environment, as shown in Fig. 12b. We place the AP on top of the shelter. To construct an offline
histogram fingerprint, we gathered data first thing in the morning when no one was in the lab. This offline training period lasts only one minute. Then, for the purpose of motion detection, we generated two test sets, including a static set and a motion set, each containing 300 testing cases. For each testing case, we measured CSIs for about 30 s, and selected the CSIs of the first 1000 packets as one test sample. The total time cost of the data collection was about 5 h.

To construct the static test set, we collect all 300 test cases over three days, of which the first two days were consecutive and the third was three days later. Each day, we measured 40 cases in the morning and 30 in the afternoon and evening, respectively.

In order to evaluate the robustness and sensitivity of R-PMD in different walking areas, we divided the lab into nine walking areas, as shown in Fig. 13, and gathered data while an individual walked back and forth in each area, for a total of 30 test cases in each. We collected these dynamic data during different periods of different days. In addition, we collected 30 test cases while an individual walked randomly across the entire lab.

To be concise, we denoted the method we used in our previous work\[14\] as “WMA” and the method we used in this study as “WMA+PCA”. We focused on the following main metrics to evaluate our detection scheme: (1) True Positive (TP) for the probability that the human motion events are correctly detected; (2) False Positive (FP) for the fraction of cases in which the system announced a “detected” event when there was no one moving; (3) True Negative (TN) for the probability that the static environment was correctly detected; (4) False Negative (FN) for the fraction of cases in which the system failed to detect human motion.

6.2 Performance evaluation

6.2.1 Impact of different combinations of receiver antennas

Figure 14 shows the effect of different antenna combinations on the detection accuracy. We can see that different combinations lead to different detection rates, due to the noisy wireless channel and the different multipath effects encountered by the packets received at different antennas. Taking into account both TP and TN, we found that antenna A alone performed the worst in both schemes, whereas the combination of antennas B and C achieved the best overall performance. Therefore, this indicates that antenna A is a “bad” antenna and directly using more antennas does not necessarily result in better performance. Also, “WMA+PCA” is more dependent on the antenna combination than “WMA”,

Fig. 12 Experimental equipment and area.

Fig. 13 Floor plan and division of areas in the laboratory.

Fig. 14 Effect of different combinations of receiver antennas (A, B, C) on detection accuracy.
as shown in the low TN rates of antenna combinations AB and AC in Fig. 14b. This is because “WMA+PCA” adopts only two principal components for human detection whereas “WMA” benefits from the frequency diversity provided by all 30 subcarriers. Based on these results, we discarded antenna A and used the combination of antennas B and C for our evaluation below.

6.2.2 Impact of different sliding window sizes
Sliding window size plays an important role in striking a balance between FP and FN. Figure 15 shows the FP and FN results of our test set with regard to different window sizes \( l \). As illustrated in the figure, choosing too small a window size leads to a high FN rate, as the variance is too small to be distinguished from that of the static environment, while choosing a very large window size results in a high FP rate, as too much noise can scramble the system. To balance the FP and FN, we set the sliding window size to be 30 packets for “WMA” and 20 packets for “WMA+PCA”. Compared with “WMA”, “WMA+PCA” requires a smaller window size since it captures more representative variation features by PCA.

6.2.3 Impact of number of principal components
The number of principal components used for feature extraction represents a tradeoff between detection performance and computational complexity. Figure 16 shows the detection rates of our test set when using different numbers of principal components. As shown in the figure, the TP increased with an increased number of principal components, whereas the TN suffered a decline. This is because that although using more principal components involves more human-motion-induced signal variation for better detection, some variations caused by unavoidable static environment changes are also captured and result in false alarms. Therefore, to balance the TP and TN, we selected the first two principal components, i.e., \( P_2 \) and \( P_3 \), for our evaluation below.

6.2.4 Overall performance
To quantitatively evaluate the overall performance of R-PMD, we used a Receiver Operating Characteristic (ROC) curve to plot the detection rate of human motion against the probability of false alarm. The ROC curve graphically reveals the inherent tradeoff between FP and TP over a wide range of thresholds. Figure 17 presents the ROCs of our test set for R-PMD and FIMD, respectively. From the figure, two things are obvious: (1) FIMD performed poorly in our test set that spans the entire lab with only one individual walking in both LOS and NLOS areas, which verifies its inapplicability for reliable indoor human detection. (2) “WMA+PCA” outperformed both “WMA” and FIMD, showing the best detection performance, and even achieved a TP rate of 88.33% with an FP rate of 0.67%. These results demonstrate the effectiveness of our PCA-based filtering technique and the superiority of our principal component variance-based features.
6.2.5 Detection performance with regard to different areas

Above, we compared the overall performance of R-PMD and FIMD. In this section, we compare the detection performance of R-PMD and FIMD in different walking areas. We divided the lab into nine walking areas from A to I, as depicted in Fig. 13. Figure 18a shows plots of the TP rate in different walking areas, where R refers to an individual walking randomly across the whole lab. From the figure, we can make two observations: (1) FIMD performs well in areas C, F, and I but suffers significant performance degradation in the other areas. This is because C, F, and I are in the LOS while the others are in NLOS areas, as shown in Fig. 13. The TP rate of test set R further verifies that FIMD is only effective in LOS areas and is unsuitable for the detection of humans exhibiting random moving patterns. (2) The TP rate of R-PMD far exceeds FIMD in all areas and “WMA+PCA” performs the best, thereby confirming the advantage of using PCA. We also note that R-PMD achieves excellent performance in all areas except in area B. This is because area B is far away from both the transmitter and receiver, resulting in less noticeable signal variation from human motion.

Since a qualified motion detection system must not only have a high TP rate but also a low FP rate, we also evaluated the FP of our test set corresponding to Fig. 18a. Figure 18 shows the results, from which we can clearly see that “WMA+PCA” achieves better performance than “WMA”, and that both methods are superior in performance to FIMD.

The above experimental results verify that R-PMD is superior to FIMD, demonstrating obvious advantages in both the TP and FP rates. We can also enhance the detection performance of R-PMD by achieving less system complexity by employing PCA-based filtering and feature extraction techniques. In summary, R-PMD is a robust system that can provide satisfactory detection performance across the entire lab.

7 Discussion

Below, we discuss some limitations and possible augmentations of R-PMD.

Pre-calibration. Although R-PMD does not involve sophisticated training, a pre-calibrated optimal threshold would be desirable. Since we have only tested our system in one important scenario, in the near future we envision a unified threshold that would fit more scenarios.

Detection performance enhancement based on receiver sensitivity. Since there were some dead spots in the area of interest, such as the area B in our experiment, deploying R-PMD in a scenario larger than our laboratory will require more TX-RX links to maintain good detection performance. However, since there are usually a small number of devices, typically one AP, installed in a large class of scenarios such as homes, an alternative approach might be to study the sensitivity of the receiver, as explored in Refs. [29, 30], and to improve system performance by choosing the best receiver location and multipath adaptation.

Detection performance enhancement based on phase information. In this study, we only leveraged CSI amplitude for DfP detection, and ignored the sensitive phase information. Although the authors in Refs. [18, 20] demonstrated that phase information is similarly or even more sensitive to environmental changes, they only tested their systems at 2.4 GHz, for which the Intel 5300 NIC is reported to have a firmware issue[24]. We plan to extend R-PMD to the phase domain to achieve better performance with other NICs or in the 5-GHz bands in our future work.
8 Conclusion

In this paper, we explored physical-layer CSI to realize a robust DfP detection system, R-PMD, using commodity WiFi devices. Noticing that existing eigenvalue-based systems have limitations that constrain their applications to only line-of-sight areas or that involve more than one individual, we proposed to leverage the human motion-induced variation on CSI and extract a robust feature for human detection. To achieve this, we analyzed the limitations of traditional low-pass filtering in data denoising and adopted a novel PCA-based filtering technique to improve denoising performance and capture the representative signals of human motion. Specifically, we first processed raw CSI with a data preprocessing module, including outlier removal, interpolation, low-pass filtering, and PCA-based filtering. Then we chose the second and third principal components as the filtered data. Next, we extracted the variance histogram as the sensitive metric for human detection and employed the EMD algorithm to infer the environmental state. Considering the different sensing quality of each antenna in modern MIMO systems, we evaluated the detection performance of different combinations of antennas and chose the best combination for better detection. Extensive experiments in a multipath-rich lab demonstrated the superiority of R-PMD over existing methods, with an average TP rate of 96.33% and FP rate of 3.67%. In addition, a comparison of our proposed R-PMD with the CSI-based FIMD and our previous method validates the effectiveness and robustness of our proposed PCA-based filtering and feature extraction schemes.

Acknowledgment

This work was supported by the National Natural Science Foundation of China (Nos. 61373137, 61572261, 61572260, and 61373017), Major Program of Jiangsu Higher Education Institutions (No. 14KJA520002), and Graduate Student Research Innovation Project (Nos. KYLX16_0666 and KYLX16_0670).

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