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Robust WLAN-Based Indoor Intrusion Detection Using PHY Layer Information

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ABSTRACT Intrusion detection techniques are widely used to guarantee the security of people's possessions. With the rapid development of wireless communication, device-free passive human detection based on wireless techniques may have more opportunities in intrusion detection. WiFi has been widely deployed in both public and private areas, which can be used as generalized sensors to detect human motion beyond communication. As a result, there have been several researches on WLAN-based motion detection. However, the detection accuracy of previous approaches declines significantly when people's moving speed becomes very slow. In this paper, we explore a novel method which has a relative stable detection performance under different moving speeds. We extract a novel feature representing the fluctuation of the whole channel from channel state information at the physical layer of 802.11n wireless networks, and utilize a probability technique to detect human motion. A hidden Markov model is leveraged as the classifier to make human detection a probability problem. We implement the system using off-the-shelf WiFi devices and evaluate it in two scenarios. As indicated in the evaluation results, our approach is an appropriate method for intrusion detection.

INDEX TERMS Device-free passive, intrusion detection, channel state information, dynamic speed.

I. INTRODUCTION

Device-free passive human detection has attracted much attention in recent years. It can detect whether there exists any people in the area of interest without requiring the people to use any electronic instruments [1], [2]. The wireless-based human detection techniques that utilize off-the-shelf infrastructure make it more pervasive. Intrusion detection [3], border protection, smart homes [4]–[8], human identification [9], [10] and elderly healthcare [11], [12] are some representative applications of device-free human detection. In these applications, it is unlikely that any devices are attached to the people during the detection process. As a result, device-free detection makes these applications more applicable and does not have the problem of sensing coverage [13], [14] and key management [15]–[17] compared with sensor-based approaches. Device-free passive entity detection plays a fundamental role in intrusion detection systems. There already exist several approaches that can provide a good detection accuracy such as video-based, infrared-based, RFID, and UWB. However, they have many limitations that hinder their wide deployment. One of the biggest limitations is that they all need dedicated devices and specific using conditions such as LOS and enough light. The video-based approaches especially have the drawback of missing privacy. A brief review discusses the advantages and drawbacks of different WSN-based localization and tracking approaches [18].

There has been increasing interest in employing WLAN-based entity detection methods in recent years for their cost-effectiveness and high accuracy. WLAN can be utilized as a generalized heterogeneous sensor network [19]–[21]. A typical WLAN-based entity detection system contains transmitters, receivers and an application server processing the collected data. WLAN-based device-free detection approaches only need WiFi transceivers that have already been widely deployed in an indoor environment compared with the approaches based on infrared, cameras, etc. Human motion can result in fluctuation of signal strength, which is the rationale of wireless-based human detection [22]. Earlier WLAN-based device-free entity detection systems extract features from the received signal strength indicator (RSSI) in the MAC layer due to its handy accessibility. RSSI is a coarse-grained and low-resolution measurement especially when the human body is away from the LOS. Wireless signals suffer from rich multipath effect in indoor environments, and RSSI is unstable when background noise exists. Recently, numerous researches explore PHY layer information of wireless networks to detect human presence. Channel state information (CSI) from PHY layer is a fine-grained measurement, and it has the advantage of being more sensitive to the changes in the monitoring area, while having little fluctuation in static environments [23], [24]. Additionally, it can be extracted from certain NICs with little firmware modifications [25]. CSI contains the information of the subcarriers in the OFDM framework, and has great improvements in detection accuracy compared to RSSI.

The impact of human motion on wireless signal becomes smaller as the moving speed slows down. Previous approaches utilize the information from only one subcarrier of the channel, which is not always sensitive enough to capture very slow motion due to multipath effect. These systems do not consider the impact of an entity's dynamic speed on detection performance. In practice, however, the intruder may move at dynamic speed when approaching different areas of the house. Therefore, previous methods are not proper for intrusion detection systems.

Based on the above challenges, in this paper, we leverage the information of the whole channel in PHY layer to implement a Speed Independent device-free Entity Detection (SIED) system that can accurately detect human motion. The detection accuracy is less affected by people's moving speed. It models the channel fluctuation using a novel feature and detects human presence utilizing a Hidden Markov Model (HMM). In this way, we make human detection a probability problem. Furthermore, it requires little calibration overhead, which results in independence of indoor scenarios. It is evaluated in two scenarios, one of which is a typical laboratory with numerous multipaths, while the other is a meeting room with fewer multipaths. This paper is an extended version of our previous work [26]; we evaluate SIED from more aspects to verify its feasibility in human detection. The evaluation results indicate that SIED can achieve a high detection accuracy when a person is moving at different speeds.

In summary, the main contributions of SIED are summarized as follows:

- We propose a human detection approach utilizing the fine-grained CSI from PHY layer that can detect humans of different moving speeds. To the best of our knowledge, SIED is the first intrusion detection system where people's moving speed has a non-significant influence on detection accuracy.
- We extract a novel feature from the whole channel and leverage a probability based classifier HMM. It is more sensitive to human motion and has more robustness to burst noise.
- We implement SIED using commodity WiFi devices and evaluate it in two real scenarios. The results indicate that it can effectively detect human motion and be practical in intrusion detection.

The outline of the rest of the paper is as follows. In Section II, the related work of entity detection is briefly reviewed. In Section III, we present a brief preliminary about device-free entity detection. The detailed description of SIED is presented in Section IV, and Section V gives the experimental settings and evaluation results. Discussion is presented in Section VI including the limitations and future work of this paper. Finally, the conclusion of our work is given in Section VII.

II. RELATED WORK

Device-free localization technique has attracted much attention recently, as it has the ability to detect human presence and even identify the identity in the monitoring area. Furthermore, the user does not have to carry any devices [1]. Entity detection is a fundamental component in the process of localization. Usually there are transmitters, receivers and an application server included in a typical WLAN-based human detection system. APs can act as transmitters and WiFi enabled devices act as receivers (MPs). The application server processes the collected signals and runs the human detection system. Received Signal Strength Indicator (RSSI) is first utilized in WLAN-based human detection, and has attracted much interest in human detection in recent years, as it is easy to obtain. But, it has some disadvantages because it is a coarse-grained measurement and unstable in static environment. It also suffers from a severe multipath effect in indoor scenarios; as a result of this, it is not sensitive enough to human motion. To overcome the disadvantages of RSSI, researchers are working hard on CSI to achieve device-free passive indoor localization. In this section, related work about passive entity detection is briefly reviewed.

A. RSSI-BASED DETECTION

Human presence has an impact on the received signal strength. Moussa and Youssef [22] applied an approach based on the Maximum Likelihood Estimator (MLE) to increase detection precision in real environments. Existing RSS-based device-free detection approaches primarily focus on RSS changes due to human presence and movements. RSS can not only be extracted from WiFi devices, but can also be extracted from ZigBee devices or other wireless sensors. In [27], Jie *et al.* considered different intrusion indicators and proposed a joint learning method to enhance the performance of the detection system. They extracted RSS from ZigBee devices and utilized a clustering method to effectively identify the presence of intruders. The localization and tracking problem was reformulated based on an inverse source by exploiting RSS values obtained from WSN nodes in [28]. RASID is a robust detection approach that can adapt to changes in the detection environment [29]. It used several modules for statistical human detection that improved the performance of detection. Another well-known RSS-based passive entity detection scheme is Radio Tomographic

Imaging (RTI) [30]–[32]. It improves the performance of RSS-based schemes by deploying a sensor network to capture the attenuation of RSS in the area of interest to detect and localize an entity. It can detect intruders with high detection rates and few false alarms. Recently, several varieties of RTI-based techniques have been developed, including the vRTI [33], kRTI [34], and dRTI [35]. Xiuyuan Zheng et al. found that the localization accuracy degraded significantly when the entity's moving speed was dynamic. In [36], they proposed a framework to improve the human detection and localization performance according to the estimated moving speed. It can adjust the time-window size adaptively based on speed change detection results. To achieve a higher performance, most RSS-based detection systems only deploy networks with multiple transmitter-receiver pairs to detect human presence. However, it raises the cost of labor and instruments.

B. CSI-BASED DETECTION

As indicated in [25], CSI can be extracted from devices equipped with commodity NICs, and only some slight firmware modification is required so that CSI-based passive detection approaches attract much attention in recent years. CSI is a channel measurement at the granularity of sub-carrier level in the framework of OFDM techniques. Most CSI-based schemes treat CSI as extended RSS. In [37], Liu *et al.* extracted the variance of CSI amplitude features to detect human motion. Pilot utilized the correlations of CSI at different times to detect human motion and determined the location of the subject [38]. There exists a burst pattern of CSI when there is someone moving in the area of wireless signals. FIMD clustered on the largest eigenvalues of the similarity matrix of CSIs that can find human presence at a high accuracy [39]. Omni-PHD virtually tuned the detection coverage into a omnidirectional disk-like range area [40]. PADS combined the amplitude and phase information of CSI to extract features to make the human detection system more sensitive, and it achieved in detecting humans moving at different speeds [41]. DeMan took advantages of both amplitude and phase information of CSI, and used different features to detect the moving and stationary human [42]. It considered breathing as the intrinsic indicator of stationary human presence. FCC extracted the variance of CSI and explored the relationship between it and the number of moving entities to achieve counting crowd [43]. FRID proposed a calibration-free human motion detection system, which could not be affected by the indoor scenarios and was free of pre-calibration or normal profile [44].

In summary, RSS-based approaches suffer from severe multipath effects in indoor environments and cannot distinguish different paths. As a result, RSS is a coarse-grained measurement of wireless signal. Fortunately, CSI can be extracted from some commodity wireless NICs and used as a much finer-grained measurement. However, existing approaches fail to detect human presence when the moving speed is very slow, which is a fatal disadvantage for intrusion detection systems. SIED, on one hand, captures the fluctuation of the wireless channel at PHY layer level as a more sensitive feature to human motion. On the other hand, it utilizes an HMM, which is a probability technique to solve the human detection problem, and makes it more accurate in human detection.

III. PRELIMINARY

A. CHANNEL IMPULSE RESPONSE

In a common indoor scenario, the wireless signal propagates through multiple paths to the receiver as shown in Fig. 1. An LOS path and several reflection paths may exist, and the received signal is the superposition of the signals from the different paths. In OFDM systems, the wireless channel in the time domain can be descripted by a channel impulse response (CIR) to distinguish different paths. Under the assumption of time-invariant, CIR can be expressed as:

$$h(\tau) = \sum_{i=1}^{N} \alpha_i e^{-j\theta_i} \delta(\tau - \tau_i) + n(\tau) \tag{1}$$

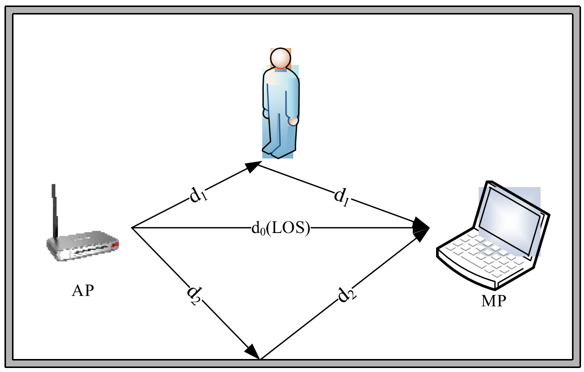

FIGURE 1. The path of wireless signal transmitting.

where

$\alpha_i, \theta_i, \tau_i$ denote the amplitude, phase and time delay of the signal from i^{th} path, respectively,

N is the total number of paths,

$n(\tau)$ is complex Gaussian white noise,

$\delta(\tau)$ is the Dirac delta function.

However, the RSSI, which is a measurement of MAC layer, fails to capture this multipath effect since it is the superposition of multipath signals. As a result, the performance of RSSI-based approaches may degrade under some conditions. To fully depict the paths, CIR can be utilized to model the wireless propagation channel, but precise CIR cannot be extracted from ordinary commodity infrastructures which is inapplicable in a home environment.

B. CHANNEL FREQUENCY RESPONSE

To overcome the above limitations, in the frequency domain, Channel Frequency Response (CFR) can model the transmitting channel, which is composed of an amplitude-frequency response and a phase-frequency response [40]. Given infinite bandwidth, CIR is equivalent to CFR, and CFR can be derived by taking the Fast Fourier Transform (FFT) of CIR.

$$H = FFT(h(\tau)) \tag{2}$$

In the 802.11n wireless network, the spacing between two adjacent subcarriers is 312.5KHz, which is balanced between hardware cost and network throughput. The Linux kernel driver of Intel 5300 NIC can be slightly modified to make it convenient to obtain CFRs for $N = 30$ subcarriers in the format of CSI:

$$H = [H(f_1), H(f_2), \ldots, H(f_N)] \tag{3}$$

The amplitude and phase of a subcarrier can be described by CSI:

$$H(f_k) = \|H(f_k)\|\, e^{j\sin(\angle H)} \tag{4}$$

where $H(f_k)$ is the CSI of the subcarrier of which the central frequency is f_k, and $\angle H$ denotes its phase. Therefore, a group of CSIs $H(f_k)$, $(k = 1, \ldots, K)$, reveals K sampled CFRs at the granularity of subcarrier level [45].

Unlike RSSI, CSI consists of both the amplitude and phase information of a subcarrier. As a result, compared to RSSI, CSI is a finer-grained measurement, and it is the CSI's intrinsic property that it has the ability to distinguish multipath components at subcarrier level [46]. Furthermore, the amplitude information is sensitive enough to extract features to detect human motion. Therefore, we leverage CSI to detect moving entities.

IV. DETECTION OF HUMAN MOTION OF DIFFERENT MOVING SPEEDS

In this section, the detailed design of our Speed Independent Entity Detection system, SIED, is described. It contains an offline training phase and an online detection phase. The architecture of SIED is shown in Fig. 2.

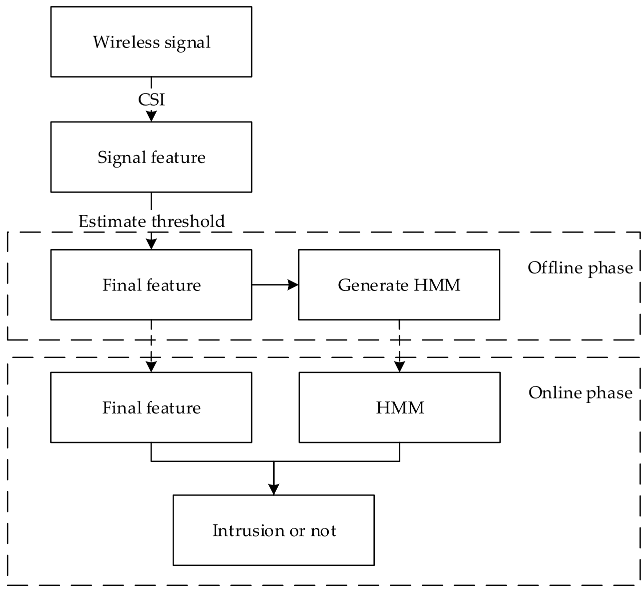

FIGURE 2. SIED's architecture.

A. FEATURE EXTRACTION

A proper feature brings great benefit in device-free passive entity detection. Consequently, feature extraction is the most important part of SIED. The MIMO technique is used in 802.11n wireless networks and multiple antennas transmit data simultaneously. The modified firmware of *CSI tools* can be used to obtain a 3-demensional matrix of $m \times n \times 30$ composed of the raw CSIs, in which m is the number of transmitter antennas and n is the number of receiver antennas, while we can extract CSIs of 30 subcarriers from the firmware.

Using multiple antennas is an effective method to improve the detection performance, which will lead to a higher computation complex. Consequently, data fusion is the first step in feature extraction. The median amplitudes of CSI are chosen as the final amplitudes, which are from the subcarriers of the same frequency.

An appropriate feature is extracted from these CFRs after data fusion. During our research, we find that human motion has different impacts on CSIs of different subcarriers. However, previous works only use the information of one subcarrier. It results in performance decreasing when people's moving speed is very slow. Many features are explored, and we finally found that the distribution of the variance of variances of CFRs of the subcarriers across the whole channel is different when the subject's moving speed varies, as shown in Fig. 3. This feature reflects the fluctuation of the whole wireless channel. It indicates that the distribution of the variance in static environment is different from that of fast and slow cases, while having overlapping parts with that of very slow cases. The overlapping parts may lead to false detection. Thus, a feasible method should be leveraged to handle it.

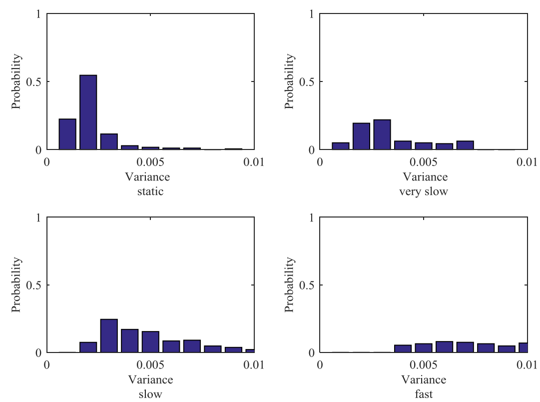

FIGURE 3. Distribution of variance of variances of different subcarriers.

Concretely, the successive CFRs are first processed starting from H_k using a sliding window with the length of n; the CSIs can be expressed as:

$$\mathbf{H} = [H_k, H_{k+1}, \ldots, H_{k+n-1}] \tag{5}$$

where $\mathbf{H}$ is a $30 \times n$ matrix that contains the CSIs within a certain window. The variance of the amplitudes of subcarrier i

within the sliding window of length n can be calculated as:

$$v_i = \mathrm{var}(\left|H_{i,k}\right|, \left|H_{i,k+1}\right|, \ldots, \left|H_{i,k+n-1}\right|) \tag{6}$$

Next, the fluctuation of the channel is calculated. A 30×1 vector that consists of the variance of the amplitudes of each subcarrier in a certain sliding window can be expressed as:

$$\mathbf{V}_w = [v_1, v_2, \ldots, v_{30}]^{\mathrm{T}} \tag{7}$$

Finally we can easily calculate the variance of all subcarriers $\mathbf{V}$ that represents the fluctuation of the wireless channel:

$$\mathbf{V} = \mathrm{var}(\mathbf{V}_w) \tag{8}$$

As can be seen from Fig. 3, the distribution of the variance is much wider when human motion exists. Therefore, when someone is moving in the monitoring area, $\mathbf{V}$ has a higher probability to be larger. As a result, the feature we extracted is sensitive to human motion.

B. ENTITY DETECTION

Like most of the entity detection systems, SIED also contains an offline training phase and an online detection phase.

1) OFFLINE TRAINING PHASE

Human detection is the core module of SIED. In the offline training phase, the training data are collected when there is nobody in the monitoring area, and the entity's moving speed is fast, slow, and very slow, respectively. The goal of the system is to reduce the impact of the overlapping parts of variance between that of static and very slow in order to achieve a higher detection accuracy. As a result, we combine a threshold based scheme with Hidden Markov Model (HMM), which utilizes probability techniques to solve human detection. The threshold is based on the feature of the training data. According to the training data, SIED decides the thresholds to segment variance values. The segment values act as the observed states that can be directly used by HMM in the online detection phase.

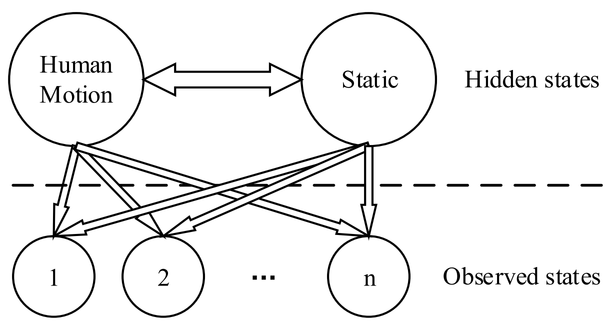

FIGURE 4. HMM for SIED.

We use an HMM as the classifier of our human motion detection system. It is assumed that in the system there are two hidden states, which are someone that is moving or someone that is static, as shown in Fig. 4. The two hidden states may exchange in the monitoring area with a certain probability. Fortunately, HMM is an appropriate tool to handle probability problems of state transition. HMM is widely used in many kinds of pattern recognition problems, for it has a good performance in speech recognition and handwriting recognition. Similar to speech recognition, HMM can also be utilized in intrusion detection, which is a special case of entity detection, as several states under human presence exist. The observed feature values of HMM in intrusion detection are corresponding to the states of human motion or static, and we assume that they are generated by a Markov model.

In this HMM, the processed feature values can be seen as observed states, while the states that generate those feature values are hidden states. In other words, the variances can be observed, but whether any human motion exists cannot be observed. Fortunately, some probability relationships exist between the variances and presence of humans. In other words, whether someone is moving can be estimated via the probability. The number of observed states needs to be decided, and a group of thresholds is utilized to divide the variances into several segments. SIED tries several combinations of the number of states and the group of thresholds, and the number of states that provides the best performance is selected. As a result, the feature values are divided into n segments, which are used as the final feature values since only finite states can be processed by HMM, and the value of n that is selected is usually between 4 and 7 to avoid a high complexity. Intuitively, the observed states in a static environment are 1 or 2 in a large extent while they are distributed throughout the observed states when the entity is moving.

The parameters of HMM are also trained in the offline phase. The parameters of HMM include state transition probability and observation symbol probability. To estimate the parameters of the HMM, SIED uses the well-known Maximum Likelihood Estimation algorithm. First, the statistic of the feature values of all the sliding windows of CSI sequences is calculated. The numbers of each feature value are divided by the total number of the sequence, and the results constitute the observation symbol matrix. The estimation of observation symbol probability when the observation is k under state j is shown in (9):

$$b_j(k) = \frac{B_{jk}}{\sum_{k=1}^{n} B_{jk}}, \quad j = 1, 2;\ k = 1, \ldots, n \tag{9}$$

where B_{jk} is the number of observations of k under state j in the training dataset.

The elements in the transition matrix are the transition probabilities between the hidden states, which are assigned intuitively for simplicity. Furthermore, we have tried many different combinations of parameters in different environments, and it is guaranteed that the models can adapt to different scenarios.

2) ONLINE DETECTION PHASE

After offline training, the HMM has been trained and SIED is ready to detect intrusion. In the online detection phase, we put the AP and MP at the same position and collect data using the same sampling rate as that in the offline training phase. The same feature is also extracted from the collected data. The Viterbi algorithm is utilized combining the trained HMM, and feature values to estimate the probabilities of hidden states from the collected CSI sequences in order to decide whether someone is moving in the monitoring area. If the probability that there exists human motion is larger than that of static, the system alarms that intrusion exists, otherwise, no alarm is reported.

V. EXPERIMENT AND EVALUATION

In this section, we will implement detailed experiments and evaluations on SIED.

A. EXPERIMENTAL SETUP

We evaluate the performance of our system with real experiments in a laboratory and a meeting room, which are two typical scenarios as indicated in Fig. 5. There are several desks with glass dam-boards and chairs in the laboratory and some other furniture in the meeting room that creates various multipath effects. There is NLOS transmission in the laboratory and LOS transmission in the meeting room. Specifically, a FAST FW150RW wireless router with a single antenna is used as the AP, while a Lenovo laptop equipped with a three-antenna Intel WiFi Link 5300 NIC running Ubuntu 10.04 LTS OS is used as the MP. The firmware of the NIC is modified to extract CSIs from data packets using the *CSI tools*. The transmitter and receiver are placed about 0.7 m above the floor and 4 m to 10 m away from each other in different scenarios.

The sensing data is collected when the AP is sending ICMP packets with the transmission rate configured to 20 Hz. At the same time, a person walks back and forth in the monitoring area at different moving speeds without anyone else in the room. The data is collected for a few cycles, each of which contains 2000 packets. The speed of fast, slow, and very slow is about 1.5 m/s, 0.7 m/s and 0.2 m/s, respectively. The transition probabilities of the two hidden states of the HMM in the experiments of the two testbeds are assigned to 0.5 and 0.5.

Three evaluation metrics are used in this paper, which are false negative, false positive, and precision.

- False Negative (FN): the ratio that SIED fails to detect human motion within the monitoring area.
- False Positive (FP): the ratio that SIED detects human motion when nobody is in the monitoring area.
- Precision: the fraction that SIED correctly tells human motion or static. The precision is integrated by FN and FP that is calculated as follows:

$$Precision = 1 - \frac{FN + FP}{L} \times 100\% \tag{10}$$

where L is the number of sliding windows. Therefore, it can be seen that the precision is the overall performance of detection systems.

B. PERFORMANCE EVALUATION

1) OVERALL PERFORMANCE

First, we evaluate the precision of our system under different scenarios with the same sliding window size. The precision of SIED in the two scenarios under different moving speeds with the window size of 3 s is shown in Fig. 6. The precision

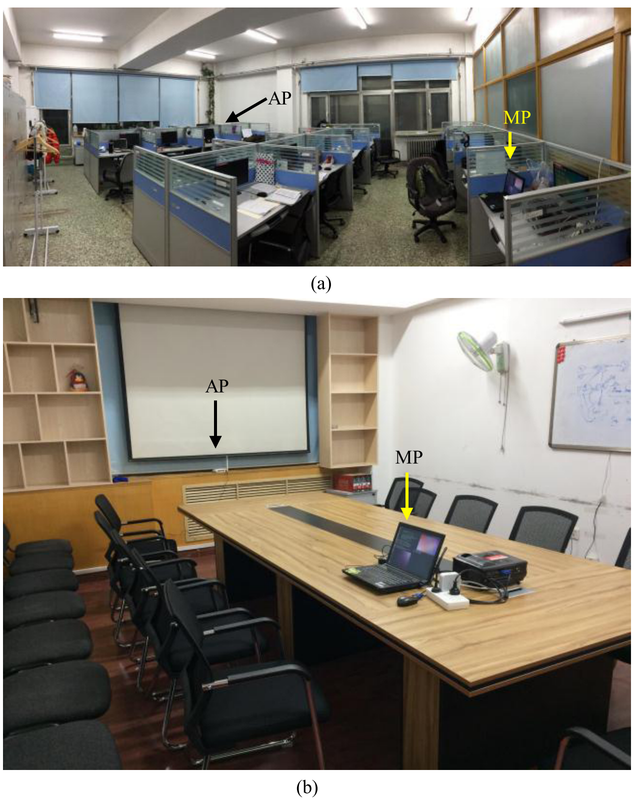

FIGURE 5. Experimental testbeds. (a) laboratory. (b) meeting room.

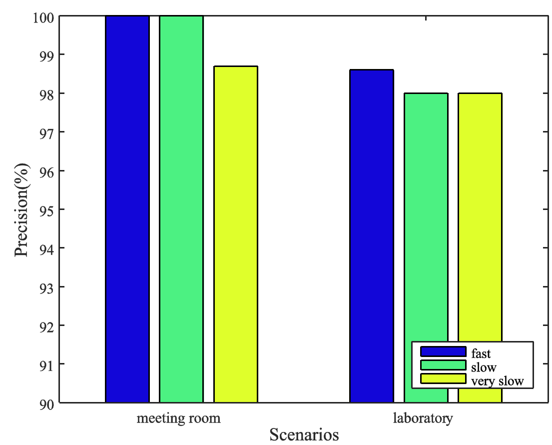

FIGURE 6. Precision of detection in different scenarios.

in both scenarios achieves higher than 98% when the human is moving under different speeds. The size of the room affects the detection precision insignificantly, and the precision has a slight decrease when SIED works in a larger room.

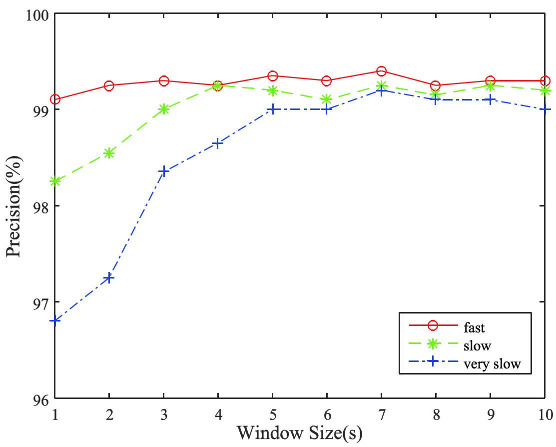

FIGURE 7. Precision of detection of different sliding window sizes.

In addition, the average precision of SIED in different window sizes in the two scenarios is presented. Fig. 7 shows the precision under different moving speeds. As shown, the precision under fast and slow speed remains relatively stable as the window size grows. The precision under the very slow speed increases as the window size grows when the window size is smaller than 6 s; it remains stable after the window size grows larger than 6s.

2) PERFORMANCE COMPARISON UNDER DIFFERENT WINDOWS SIZES

Furthermore, we also evaluate the performance compared with two other CSI-based methods: FIMD, PADS, and an RSS-based RASID-like approach under various conditions are used to research the advantages of SIED. All methods are tested under the same condition, and we have tried several combinations of parameters of these methods and select a group of parameters that produce the best results.

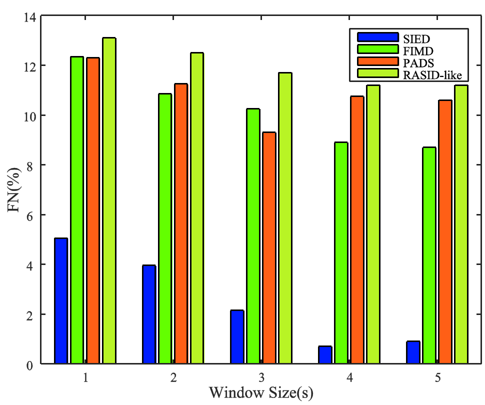

FIGURE 8. FN of SIED vs. other approaches with different window sizes.

Fig. 8 and 9 show the average FN and FP comparisons respectively when the sliding window sizes are different.

The detection under a very slow moving speed is the most difficult, and in consequence, we choose the comparison under this speed. As can be seen from Fig. 8, the approach's FN rates declines from a general view as the sliding window size grows and SIED has a better performance than the other methods. A larger window size can capture more variance that makes FN rates lower. SIED has the lowest FN rate among the four for all window sizes. The FN of RSS-based approach is higher since RSS is not sensitive enough to capture human motion when the speed is very slow.

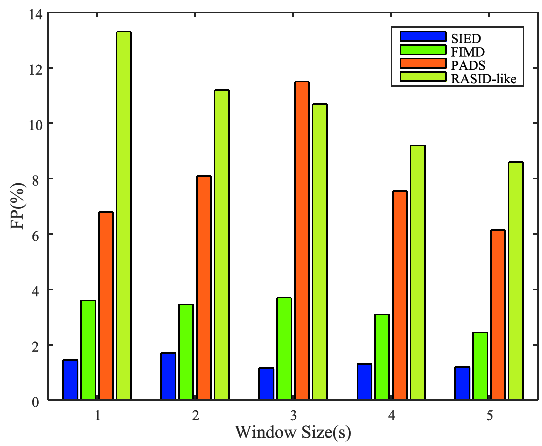

FIGURE 9. FP of SIED vs. other approaches with different window sizes.

As depicted in Fig. 9, SIED gets an FP rate below 2%, which indicates that it makes very few false alarms and its FP rate is affected non-significantly by window size. FIMD gets a slightly higher FP rates than SIED, but PADS gets a much higher FP rate of 11.5%, especially when the window size is 3 s. The peak value of PADS at window size of 3 s is because it utilizes phase information of CSI. The phase of CSI is very sensitive to environmental noise, and the effect of the noise is the most significant at that window size. The overall FP of RSS-based method is the highest among the four approaches because the feature is close to that of static when the entity's moving speed is very slow.

The comparison of average precision among the approaches when the sliding window sizes are different is shown in Fig. 10. The precision is an overall performance of the system. The precision of SIED and FIMD both have a rise as the window size gets larger. Although the performance of FIMD is better than PADS, it is a cluster-based approach and it needs to collect too many packets. As can be seen, SIED outperforms the other three approaches that confirm the feasibility of SIED. It reaches higher than 98% when the window size is 3 s. The RSS-based method can also detect human motion effectively, but the precision is not high enough for an intrusion detection system. As a result, SIED can be considered as a high performance intrusion detection system.

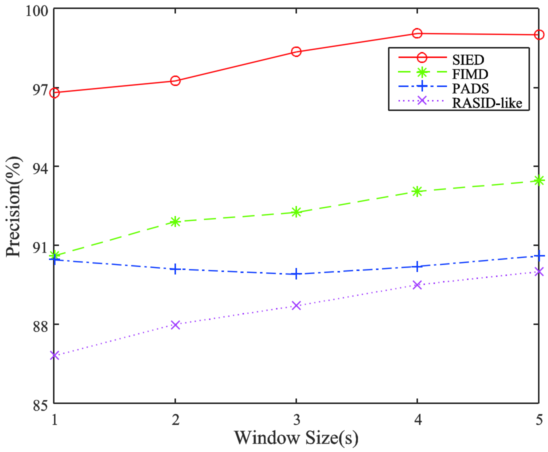

FIGURE 10. Precision of SIED vs. other approaches with different window sizes.

3) PERFORMANCE COMPARISON UNDER DIFFERENT SPEEDS

According to the experiments above, Fig. 11 shows the average FN rate of the approaches when the moving speeds are different, and the window size is 3 s. It can be seen that SIED's FN rates are the lowest among the four approaches. Even when the entity is moving at a very slow speed, the average FN rate increases to 2.1%, which is still acceptable.

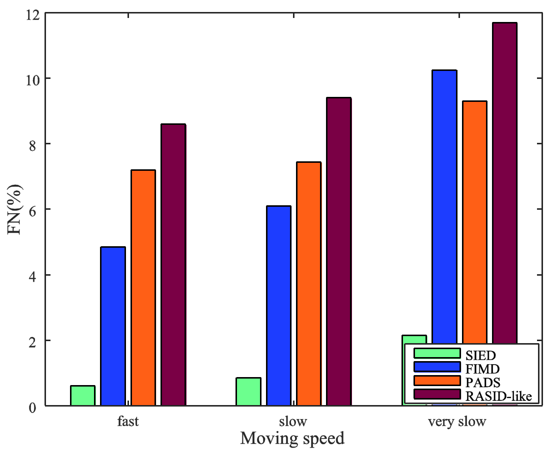

FIGURE 11. FN of SIED vs. other approaches under different moving speeds.

The comparison of average FP rates when the moving speeds are different is shown in Fig. 12. As it is indicated, the approaches all perform steadily. In addition, SIED and FIMD both have satisfactory FP rates. Nevertheless, although PADS leverages a more complicated characteristic, it obtains a much higher FP rate of about 10%. This means that PADS is more likely to make false alarms than the other methods. The RSS-based method also has a high FP rate.

The comparison of the average precision when the moving speeds are different is shown in Fig. 13. It can be seen that SIED has a higher precision than the other three approaches. All four approaches encounter a decrease in precision as

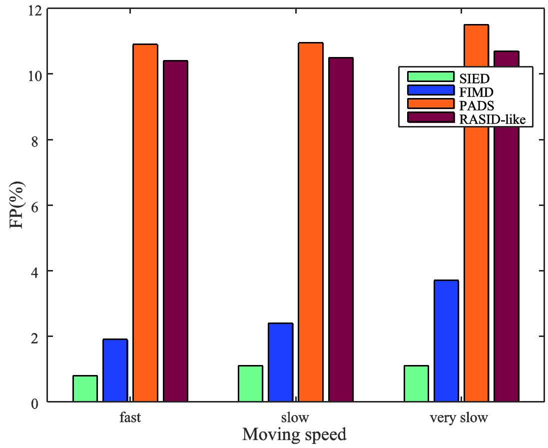

FIGURE 12. FP of SIED vs. other approaches under different moving speeds.

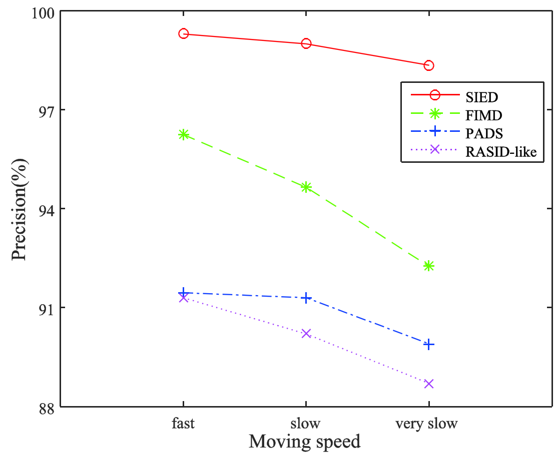

FIGURE 13. Precision of SIED vs. other approaches under different moving speeds.

the moving speed becomes slower, but SIED has the least decrease. In other words, our system has more potential to detect human motion of very slow speed.

4) PERFORMANCE COMPARISON UNDER DIFFERENT RADIUSES

We have also conducted an experiment in our laboratory to compare the performance under different radiuses. Detection range is an important criterion for intrusion detection systems. In real environments, people's walking path may have diverse distances from the MP. It is expected that the system should have a stable performance when the entity has different distances from the MP. In consequence, we perform the evaluation that gradually increases the walking radius from 1 meter to 9 meters in our lab, as shown by the dotted line in Fig. 14. It is evaluated under the moving speed of very slow and a window size of 3 s. It is more challenging that the impact of human motion gets smaller as the distance between the entity and the MP increases. An entity walks around the circumference of the circles, and the results of

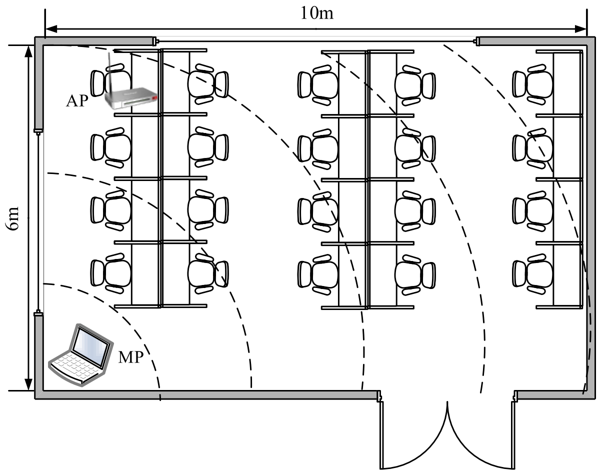

FIGURE 14. The diagram of testbed of radius experiment in the laboratory.

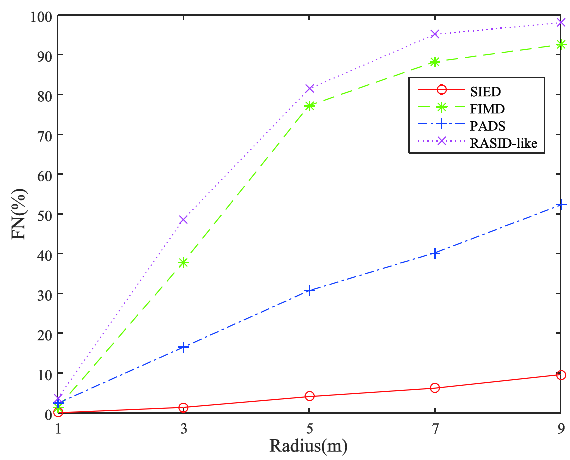

FIGURE 15. FN of SIED vs. other approaches under different radiuses.

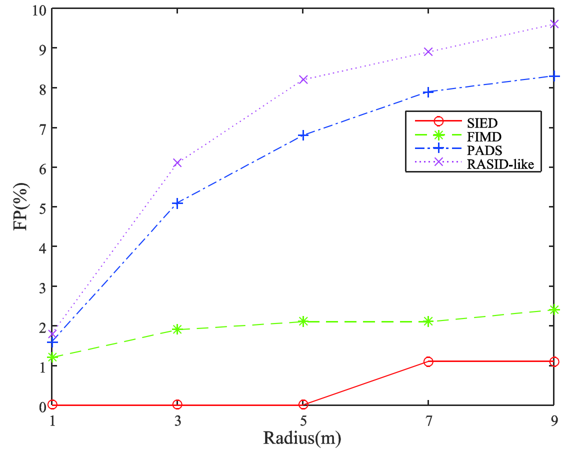

FIGURE 16. FP of SIED vs. other approaches under different radiuses.

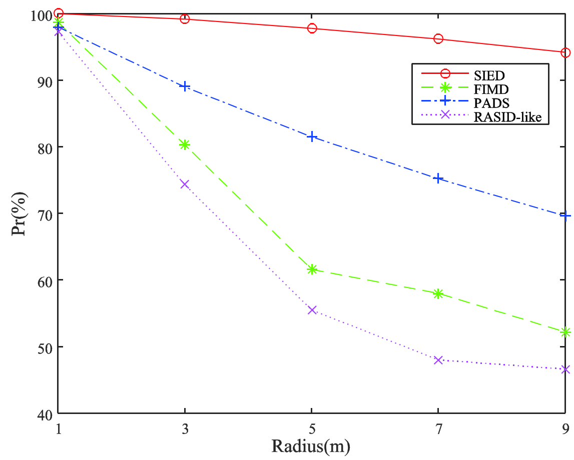

FIGURE 17. Precision of SIED vs. other approaches under different radiuses.

FN are presented in Fig. 15. As can be clearly seen, with the radiuses gradually increasing, the FN rates of FIMD, PADS, and RASID-like all raise at a very high level. The difference of FN rates of the approaches when the radius is 1 meter is insignificant. However, the difference becomes significant when the radius increases to 3 meters, especially because FIMD and RASID-like are very sensitive to radius size. The FN rates of FIMD and RASID-like even increase to about 90% when the radius increases to 7 meters and larger. The FN rate of SIED is relatively stable as the radius increases.

The results of FP are presented in Fig. 16. As can be seen, with the increasing of the radius, the FP rates of PADS and RASID-like have an increasing trend, while SIED and FIMD remains relatively stable; the FP rate of SIED is even lower among these approaches. The FP rates of the approaches are lower than their FN rates, which means they makes fewer false alarms than misdetection.

Fig. 17 shows the results of precision. It can be seen that our approach has stable performance, and the precision has only a slight decrease as the radius grows. It still has a 94% precision when the radius increases to 9 m. However, the precision of the other approaches declines significantly since the radius becomes larger than 3 m. For FIMD and RASID-like, the performance degrades especially sharply when the radius increases, and the precision decreases to less than 50% when the radius is 5 m and larger. As a result, it can be noted that SIED outperforms the other approaches.

VI. DISCUSSION

We did several evaluations in this work to demonstrate the advancement of SIED. But there still exist some limitations. In this section, we will give a discussion about the limitations and potentials of SIED that give the future direction of our work.

First, the training data of SIED needs both static and dynamic data. As a result, it is a threshold-based approach, and the threshold is likely environment-tailored. We evaluated SIED in two typical environments using the same threshold, and it is indicated that it has the potential to find a unified threshold or a scheme that can automatically calculate the threshold.

In addition, SIED is evaluated when the intruder is walking upright. However, in real scenarios, the intruder is more likely to move in an abnormal manner, which adds more challenges into the intruder detection system. Consequently, we should explore new features to model various kinds of human motion to increase the robustness of the intruder detection system.

In our future work, we will focus on exploring novel and effective features to improve the robustness of the intruder detection system.

VII. CONCLUSIONS

In this paper, a device-free intrusion detection approach SIED is proposed that the moving speed of the intruder has an insignificant effect on the detection performance. It achieves a good performance even when the human is moving at a very slow speed. Only off-the-shelf WiFi devices are required, and the feature is extracted from fine-grained CSI in wireless channels. In order to extract an effective feature, the fluctuation of the whole channel is calculated and divided into segments. Then the HMM is utilized as the classifier in human detection. SIED leverages probability techniques to achieve a more accurate detection of intrusion. Numerous experiments from various aspects have proved that SIED can effectively detect human motion, especially for human motion of very slow speed.

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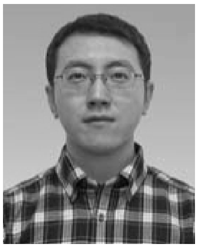

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