Robust WLAN-based Indoor Fine-grained Intrusion Detection

Jiguang Lv*, Wu Yang*, Liangyi Gong*, Dapeng Man*, Xiaojiang Du†

*Information Security Research Center, Harbin Engineering University, Harbin, China

† Department of Computer and Information Sciences, Temple University, Philadelphia, PA 19122, USA

{lvjiguang, yangwu, gongliangyi, mandapeng}@hrbeu.edu.cn, xjdu@temple.edu

Abstract—**Intrusion detection plays a critical role in security of people's possessions. Approaches such as video-based, infrared-based, RFID, UWB, etc. can provide satisfying detection accuracy. However, they all require specialized hardware deployment and strict using conditions which hinder their wide deployment. Beyond communication, WLANs can also act as generalized sensor networks and there are several researches working on motion detection via WLAN due to its advantages in deployment flexibility, coverage, and cost efficiency. Nevertheless, they are unsuitable for intrusion detection as none of them can accurately detect human motion when the moving speed is very slow. This paper proposes SIED as an accurate method for Speed Independent device-free Entity Detection which is suitable for intrusion detection even when the entity's moving speed is very slow. The influence becomes much smaller when the entity is moving with a very slow speed. Previous methods have the limitations in that their performance downgrades sharply when the entity's moving speed is very slow. Recently, it has been shown that Channel State Information (CSI) at PHY layer of wireless network has the potential to detect moving entities more accurately. In this paper we leverage CSI of 802.11n wireless network and probability technique to detect entities of different moving speeds. SIED captures the variance of variances of amplitudes of each CSI subcarrier, and combines Hidden Markov Model (HMM) to make entity detection a probability problem. We implement SIED using commercial WiFi devices and evaluate our method using two typical testbeds and show that SIED can achieve an average detection accuracy of greater than 98% under different entity moving speed.**

Keywords—device-free passive; intrusion detection; physical layer information; dynamic speed

I. INTRODUCTION

There has been an increasing interest recently in device-free detection techniques to confirm whether there exists any human movement in the area of interest without any devices attached to them [1]. Especially, the detection techniques which take advantage of the already installed wireless infrastructure, e.g. WLANs, which make entity detection more ubiquitous. Device-free detection can be used in intrusion detection [2], border protection, elderly healthcare [3, 4] and smart homes [5, 6], etc. In such applications, users are apparently not expected to wear any devices to participate actively in detection process. To make detection system applicable, we need device-free detection techniques. Especially for intrusion detection systems, device-free entity detection is the fundamental technique. Especially in intrusion detection systems, it is expected that the systems should make the false positive and false negative rates as low as possible under different moving speed. However, the impact of human motion becomes quite small when the moving speed is very slow. That makes it challenging for previous works to achieve a high accuracy under this condition. We consider entity and human as similar and they are used interchangeably in the paper.

Recently, wireless LANs (WLANs) become very popular throughout the world for ease of installation and open access [2]. Beyond communication, WLANs can also act as generalized sensor networks and it opens up a chance for device-free entity detection research. At the same time, there are many challenges. The rationale of WLAN device-free entity detection is that human movement has an effect on the signal strength [7]. A typical WLAN entity detection system usually contains APs as transmitters and WiFi enabled devices as receivers or monitoring points (MPs), and an application server that processes the signal collected by MPs to determine whether there exist any entities. Received Signal Strength Indicator (RSSI) has been widely used in WLAN device-free entity detection systems due to its handy accessibility [8-11]. Most of the systems exploit variations in RSS measurements to determine human existence. Although it has been extensively researched, RSS-based schemes still suffer from coarse granularity and are unstable to background noise because of the multipath effect. Consequently, false detection often occurs in RSS-based detection systems which makes it unfeasible.

As a result, a finer-grained solution is desired to replace RSSI to make device-free entity detection more applicable. Fortunately, some researchers find that Channel State Information (CSI) at the physical layer of wireless networks is more sensitive to human motion while keeping quite stable in static environments [12, 13] and it is now available on some commodity NICs with minimal firmware modifications [14]. CSI is a subcarrier-level channel measurement in the framework of OFDM techniques. It is now attracting more and more attention, and has the potential to make device-free entity detection more accurate. Pilot [15] leverages the correlations of CSI over time to find anomalies and locate the entity. FIMD [16] leverages the insight that CSI maintains temporal stability while exhibits burst patterns when motion takes place to accurately detect humans. Omni-PHD [17] introduces the concept of omnidirectional passive human detection which tunes the coverage into a disk-like range. PADS [18] leverages the full information of CSI including amplitudes and phases to extract features to shape into sensitive metrics for target detection and has the ability to detect humans of dynamic moving speeds. FRID [19] explores a fine-grained real-time calibration-free device-free passive human motion detection system, which is independent of indoor scenarios and needs no prior calibration and normal profile.

In real world environment, people may move at different speeds. For instance, intruders in the house may move very slow while people under emergency may move much faster. However, the researches above have the limitation that none of them have a high detection rate when the entity moves very slowly. Previous works can get high detection rates when entity's moving speed is fast or slow, but the case that the entity is moving with a very slow speed is not in their consideration. Unfortunately, it is common for an intruder to move very slowly when he breaks into a house potentially to commit a crime. When the moving speed is very slow, the effect that human motion has on wireless signal is so small that previous works cannot accurately detect the human presence. As a result, previous works are not suitable for intruder detection and it is necessary to find an approach that can detect entities when the moving speed is very slow.

In this paper, we introduce SIED as an accurate scheme for Speed Independent device-free Entity Detection which is suitable for intrusion detection. It captures the variance of variances of amplitudes of each subcarrier at PHY layer level as features and uses Hidden Markov Model (HMM) to model human motion of different speeds and detect human presence slightly influenced by moving speed. Under this scheme, we transfer the human detection problem into a probability problem. In addition, it reduces the calibration overhead that it is independent of indoor scenarios. We evaluate SIED using two typical testbeds one of which is rich in multipath effect and the other has fewer multipaths. The results show that SIED can detect human motion of different speed at a high average accuracy of greater than 98% and nearly 97% even when the moving speed is very slow, which outperforms existing approaches.

In summary, the main contributions are as follows.

1) We propose to use the fine-grained PHY layer information CSI to detect human motion of different speeds. To the best of our knowledge, it is the first approach that is suitable for intrusion detection systems even when the entity's moving speed is very slow.

2) We leverage probability scheme HMM to transfer the motion detection problem into a probability problem, which is robust to burst noise. As a result, it has a higher accuracy.

3) We present the design and implementation of SIED in commodity WiFi devices. Evaluation results show that it can detect human moving at a very high accuracy.

The rest of the paper is organized as follows. In section II, we present a brief introduction of CSI. Section III gives the details of design of SIED and experiment settings and results are presented in section IV. Finally, we conclude our work in section V.

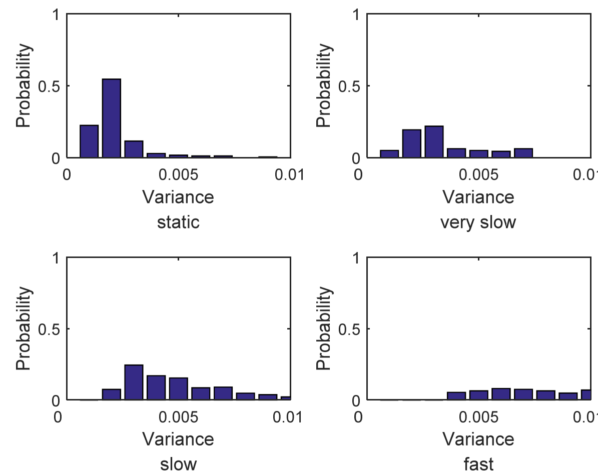

Fig. 1. Distribution of variance of variances of different subcarriers

II. PRELIMIARY

In this section, we introduce the core background of the physical layer information that constitutes our approach.

The RSSI from MAC layer is used to be the primary indicator of wireless signal property, but it is a superposition of multipath signals which suffers from harsh multipath effect in indoor environments. Consequently, RSSI can only act as a coarse-grained measurement in entity detection. To resolve this problem, some pioneer research works have explored PHY layer Channel State Information (CSI). With off-the-shelf commodity Intel 5300 NIC and a slightly modified Linux kernel driver, we can obtain a group of sampled version of Channel Frequency Responses (CFRs) for $N = 30$ subcarriers within WiFi bandwidth in the format of CSI.

$$H = [H(f_1), H(f_2), ..., H(f_N)] \tag{1}$$

Each CSI depicts the amplitude and phase of a subcarrier:

$$H(f_k) = \|H(f_k)\| e^{j\sin(\angle H)} \tag{2}$$

where $H(f_k)$ is the CSI at the subcarrier with central frequency of f_k, and $\angle H$ denotes its phase. Hence a group of CSIs $H(f_k), (\mathrm{k} = 1, ..., \mathrm{K})$, reveals K sampled CFRs at the granularity of subcarrier level [20].

Therefore, CSI is a finer-grained measurement compared to MAC layer RSSI, and can distinguish multipath components at subcarrier level [13]. In addition, only amplitudes are sufficient to extract sensitive features to detect moving entities and consequently, we choose CSI to detect human motion.

III. ENTITY DETECTION UNDER DIFFERENT SPEED

This section describes our probability approach for speed independent entity detection.

A. Feature Extraction

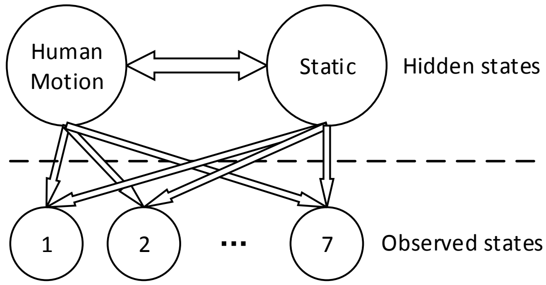

Fig. 2. HMM for SIED

A proper feature plays a critical role in device-free passive human detection. According to the modified firmware, the raw CSIs constitute a 3-demensional matrix of $m \times n \times 30$, in which m and n are the number of antennas of the transmitter and receiver end respectively, and 30 is the number of subcarriers we can obtain. Multiple antennas can be used to improve the performance of human detection, but data from a single antenna is enough to achieve high detection precision. Therefore, the first step of feature extraction is data fusion or antenna selection. We choose the median CFR amplitude from the subcarriers of the same frequency as the final CFR.

After data fusion, we are going to find an appropriate feature from these CFRs. We have explored many characteristics and find that variance of variances of CFRs of different subcarriers distributes differently when the entity's moving speed is different, as shown in Fig. 1. It is clear that the variance of statics differs from that of slow and fast, but has some overlapping parts with that of very slow. The overlapping part may cause some false detection that we need a feasible method to handle the overlapping parts which is introduced in the next subsection.

Concretely, we first process continuous CFRs starting from H_k over a sliding window of length n, the CSIs can be expressed as:

$$\mathbf{H} = [H_k, H_{k+1}, ..., H_{k+n-1}] \tag{3}$$

where $\mathbf{H}$ is a $30 \times n$ matrix, and the variance of each subcarrier over the sliding window will constitute a 30×1 vector expressed as:

$$\mathbf{V}_w = [v_1, v_2, ..., v_{30}]^{\mathrm{T}} \tag{4}$$

where v_i is the variance of subcarrier i. Next the variance of all subcarriers $\mathbf{V}$ can be easily calculated:

$$\mathbf{V} = \mathrm{var}(\mathbf{V}_w) \tag{5}$$

Therefore, when someone is moving in the area of interest, $\mathbf{V}$ is more likely to be larger.

B. Motion Detection

Motion detection is the key module of our SIED approach. Aiming at handling the overlapping feature values between static and very slow and achieving a high detection accuracy, we adopt a threshold based scheme assisted by HMM classification that transfers the motion detection into a probability problem which is more robust to environmental changes.

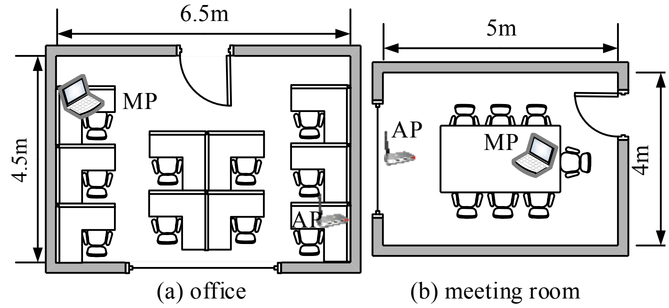

Fig. 3. Experimental testbeds.

We propose to use Hidden Markov Model (HMM) to build our entity detection system. We assume that whether there is someone moving or not are two states as shown in Fig. 2. Transitions between the two states may take chance in the area of interest. Fortunately, HMM is a suitable tool to build state transition models using time-dependent features and there always exists the transition from human motion to static or from static to human motion. HMM is widely used in many pattern recognition problems such as 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 there exist several states with human presence. The use of HMM for intrusion detection is based on the assumption that the observed feature value, corresponding to human motion or static, is generated by a Markov model.

In this HMM, the feature values can be observed while the underlying states that generated those feature values are hidden. In other words, the variances can be observed but whether there exists any human motion cannot be observed. Fortunately, there are some probability relationships between the variances and human presence and we can estimate whether there is someone moving via the probability. To decide the number of observed states, we use a group of thresholds to divide the variance values into several levels, in which the thresholds are estimated from the training data. SIED iterates through various numbers of states with the group of thresholds and selects the number that provides the highest accuracy. As a result, we divide the feature values into 7 levels as the final feature values because HMM can only handle finite states and we assume there are 7 states that can be observed. In other words, there are 7 observed states and 2 hidden states.

To estimate the state transition matrix and confusion matrix for the HMM, SIED uses the well-known Baum-Welch algorithm. A rough guess of these probabilities are needed for Baum-Welch algorithm to start with. We first make a statistic of the feature values of all the sliding windows of CSI sequences, and the numbers of each feature value are divided by the total number of the sequence as the initial probabilities of the confusion matrix. The initial probabilities of transition matrix are assigned intuitively. In addition, we have tested many times of different parameters over different environments and evaluated the models to ensure that the models do not overfit on samples from specific scenarios.

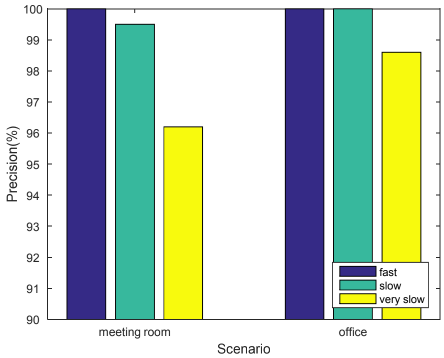

Fig. 4. Precision of detection in different scenarios

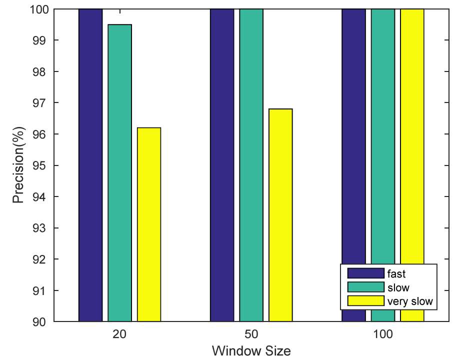

Fig. 5. Precision of detection of different sliding window sizes

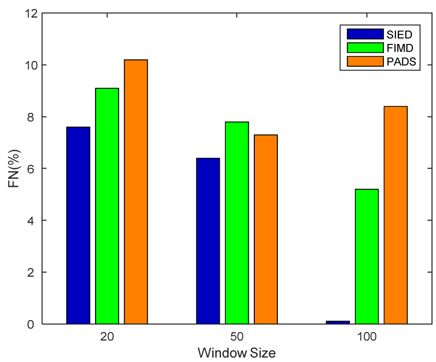

Fig. 6. FN of SIED vs. other approaches with different window sizes

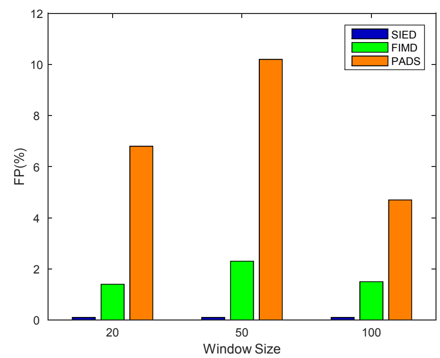

Fig. 7. FP of SIED vs. other approaches with different window sizes

After the transition matrix and confusion matrix are obtained, the Viterbi algorithm is utilized to estimate hidden states from observed CSI sequences which is to decide whether there is someone moving in the area of interest.

IV. Experiment and Evaluation

A. Experiment Setup

To evaluate the performance of SIED, we conduct real experiments in two typical testbeds, one of which is an office and the other is a meeting room as shown in Fig. 3. Each testbed is occupied with desks, chairs and other furniture creating different multipath effects. Specifically, we use the FAST FW150RW wireless router with a single antenna as the AP and a Lenovo laptop equipped with a three-antenna Intel WiFi Link 5300 (iwl 5300) NIC running Ubuntu 10.04 LTS OS as the MP. The firmware is modified to extract CSIs from data packets using the CSI tools. The transmitter and receiver are placed 0.7m to 1.2m above the floor and 4m to 6m away from each other.

During data collection period, the AP is configured to send ICMP packets at the rate of 20Hz. An entity is walking back and forth in the rooms with the speed of fast, slow, and very slow respectively without anyone else nearby for several cycles and each cycle contains 2000 packets. The speed of fast, slow, and very slow is about 1.5m/s, 0.7m/s and 0.2m/s, respectively.

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

- False Negative (FN): the fraction that the system fails to detect human motion within the area of interest.
- False Positive (FP): the fraction that the system mistakenly announces human motion when there is nobody within the area of interest.
- Precision: the probability that the system correctly recognizes human motion and static.

B. Performance Evaluation

First, we depict the precision of SIED working over different scenarios of the same sliding window size. Fig. 4 presents precision of SIED in the meeting room and office respectively with the window size of 50 under different moving speeds. The unit of window size we used in this paper is data packet, and the size of 50 is equal to 2.5s as the sampling rate in this paper is 20 Hz. The precision in both the meeting room and office achieved greater than 99% when moving fast and slow. Although it decreases a little when moving very slow, the precision can be also as high as 96.2%.

Furthermore, we present the precision of SEID in different window sizes. Fig. 5 shows the result under different moving speeds in the meeting room. Sliding window size has only an insignificant effect on the precision of SIED, and it even reaches 100% precision under all moving speeds when the window size is 100, which is 5s.

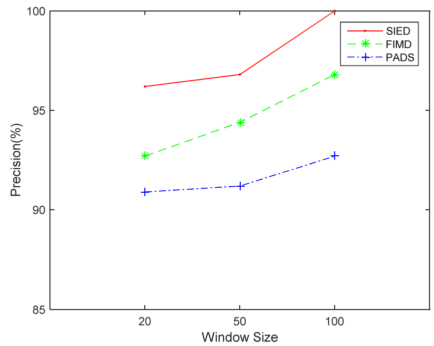

Fig. 8. Precision of SIED vs. other approaches with different window sizes

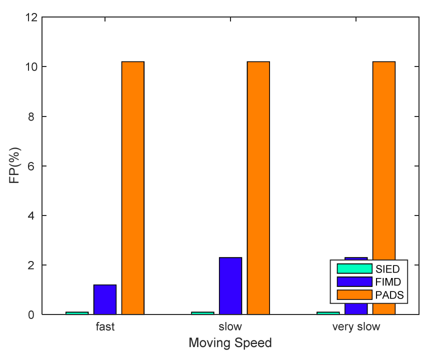

Fig. 10. FP of SIED vs. other approaches with different moving speed

In addition, to study the advancement of SIED, we also present the performance compared with FIMD and PADS under various conditions. It is worth mentioning that during the test SIED keeps the same parameters in both the meeting room and office, but FIMD and PADS have to change parameters when the environment changes. So SIED is more robust to environmental changes than the other two.

The FN comparison among the three approaches with different window sizes tested in the meeting room when the moving speed is very slow is shown in Fig. 6. We chose the comparison under very slow moving speeds because it is most difficult for the detection systems to have a good performance. The approaches' FN rates get lower as a whole as the window size gets larger, and SIED outperforms the other two approaches. SIED has the lowest FN rate among the three for all window sizes. Especially when the window size is 100, it detects all human presence and gets 0% FN rate.

The FP comparison among the three approaches with different window sizes tested in the meeting room when the moving speed is very slow is shown in Fig. 7. As can be seen, SIED and FIMD both get an FP rate below 3% which is satisfactory and SIED even gets 0% FP rate for all window sizes which means it makes no false alarms. But PADS gets a much higher FP rate of 10.2% when the window size is 50. FIMD and PADS get a little higher FP rate when the window size is 50 rather than decreasing as the window size increases.

The precision comparison among the three approaches with different window sizes tested in our meeting room when the

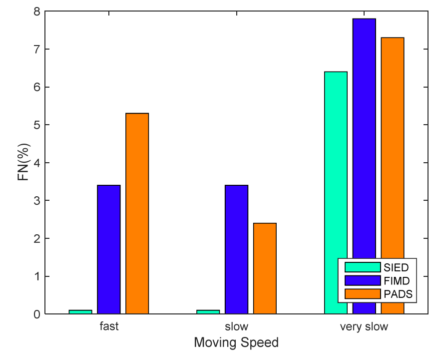

Fig. 9. FN of SIED vs. other approaches with different moving speed

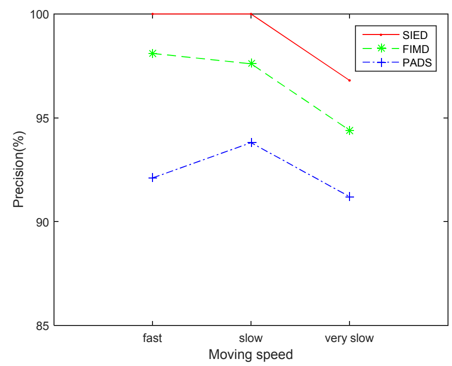

Fig. 11. Precision of SIED vs. other approaches with different moving speed

moving speed is very slow is shown in Fig. 8. The precision is integrated by FN and FP that is calculated as follows:

$$Precision = 1 - \frac{FN + FP}{L} \times 100\% \qquad (6)$$

where L is the number of sliding windows. So the precision can be seen as an overall performance of detection systems. It can be verified that the precision of the three approaches all increase as the window size gets larger and they all have a precision of greater than 90%, among which SIED's precision is greater than 95% and the precision of SIED reaches 100% when the window size is 100 in our test. In consideration of the balance between precision and time delay, it is appropriate to set the window size to 50.

According to the experiments above, the FN comparison among the three approaches under different speeds tested in the meeting room when the window size is 50 is shown in Fig. 9. It can be seen that SIED can recognize all the human presence when the entity's moving speed is fast and slow. When entity's moving speed is very slow, the FN rate has a 6.4% increase which is acceptable. SIED has the lowest FN rate for all the moving speed among the three approaches.

The FP comparison among the three approaches under different speeds tested in our meeting room is shown in Fig. 10. As can be seen, all the three approaches perform steadily, and SIED and FIMD both make satisfactory FP rate, especially SIED has 0% FP rate under all the three moving speed.

However, although PADS uses a more complicate feature, it gets a much higher FP rate of about 10%, which makes more false alarms during entity detection when there is actually no one in the area of interest at all.

The Precision comparison among the three approaches under different speeds tested in our meeting room is shown in Fig. 11. As it is indicated, the precision reflects the overall performance of the detection systems. Our SIED has a 100% precision when the entity's moving speed is fast and slow, and drops slightly to 97.6% when the moving speed is very slow. SIED has a higher precision than the other two approaches under different moving speeds. In other words, SIED is more sensitive to entities with very slow speeds than the other two approaches.

We have also compared the three approaches in the office, and the results show that SIED has a better performance of FN and FP as well compared to the other two in that environment without changing any parameter. However, FIMD and PADS both need a recalibration to get a relative good performance in another environment.

V. Conclusion and Future Works

In this paper, we propose a device-free passive human motion detection approach SIED that the entity's moving speed has a smaller impact on the performance. It is more suitable for intrusion detection as it has a high precision even when the entity's moving speed is very slow. It uses existing WLAN infrastructure and is based on fine-grained CSI from PHY layer of wireless network. We first extract the variance of variances of amplitudes of each CSI subcarrier and divide the variance into 7 levels as the feature. And then utilize the HMM as the classifier in motion detection. SIED leverages probability techniques to provide a more accurate estimation of dynamic or static.

We have implemented SIED with a commercial 802.11n NIC and conducted extensive experiments from several aspects compared with FIMD and PADS, and the evaluation results show that SIED is a simple but effective approach. Its overall precision can achieve greater than 98% for all moving speeds which corresponds to about 6% improvement over previous works.

In the next stages, we plan to improve its robustness to environmental changes and extend SIED to distinguish different moving speeds.

Acknowledgment

This research is supported by the National Natural Science Foundation of China (Grant No. 61170242, 61300206 and 61472098) and the Fundamental Research Funds for the Central Universities (Grant No. HEUCF100605).

References

[1] Youssef, M., Mah, M., and Agrawala, A.: "Challenges: device-free passive localization for wireless environments". in *Proc. Proceedings of the 13th annual ACM international conference on Mobile computing and networking*, Montreal, Quebec, Canada2007 pp. 222-229

[2] Seifeldin, M., Saeed, A., Kosba, A.E., El-Keyi, A., and Youssef, M.: "Nuzzer: A Large-Scale Device-Free Passive Localization System for Wireless Environments", *Mobile Computing, IEEE Transactions on*, 2013, 12, (7), pp. 1321-1334

[3] Han, C., Wu, K., Wang, Y., and Ni, L.M.: "WiFall: Device-free fall detection by wireless networks",in *INFOCOM, 2014 Proceedings IEEE,* 2014, pp. 271-279

[4] Xuefeng, L., Jiannong, C., Shaojie, T., and Jiaqi, W.: "Wi-Sleep: Contactless Sleep Monitoring via WiFi Signals",in *Real-Time Systems Symposium (RTSS), 2014 IEEE,* 2014, pp. 346-355

[5] Nandakumar, R., Kellogg, B., and Gollakota, S.: "Wi-Fi Gesture Recognition on Existing Devices", *arXiv preprint arXiv:1411.5394*, 2014

[6] Wang, W., Liu, A.X., Shahzad, M., Ling, K., and Lu, S.: "Understanding and Modeling of WiFi Signal Based Human Activity Recognition". in *Proc. Proceedings of the 21st Annual International Conference on Mobile Computing and Networking*, Paris, France2015 pp. 65-76

[7] Moussa, M., and Youssef, M.: "Smart devices for smart environments: Device-free passive detection in real environments",in *Pervasive Computing and Communications, 2009. PerCom 2009. IEEE International Conference on,* 2009, pp. 1-6

[8] Wilson, J., and Patwari, N.: "Radio Tomographic Imaging with Wireless Networks", *Mobile Computing, IEEE Transactions on*, 2010, 9, (5), pp. 621-632

[9] Kosba, A.E., Saeed, A., and Youssef, M.: "RASID: A robust WLAN device-free passive motion detection system",in *Pervasive Computing and Communications (PerCom), 2012 IEEE International Conference on,* 2012, pp. 180-189

[10] Zhang, D., Liu, Y., Guo, X., and Ni, L.M.: "RASS: A Real-Time, Accurate, and Scalable System for Tracking Transceiver-Free Objects", *Parallel and Distributed Systems, IEEE Transactions on*, 2013, 24, (5), pp. 996-1008

[11] Paul, A.S., Wan, E.A., Adenwala, F., Schafermeyer, E., Preiser, N., Kaye, J., and Jacobs, P.G.: "MobileRF: a robust device-free tracking system based on a hybrid neural network HMM classifier". in *Proc. Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, Seattle, Washington2014 pp. 159-170

[12] Xiao, J., Kaishun, W., Yi, Y., and Ni, L.M.: "FIFS: Fine-Grained Indoor Fingerprinting System",in *Computer Communications and Networks (ICCCN), 2012 21st International Conference on,* 2012, pp. 1-7

[13] Kaishun, W., Xiao, J., Youwen, Y., Min, G., and Ni, L.M.: "FILA: Fine-grained indoor localization",in *INFOCOM, 2012 Proceedings IEEE,* 2012, pp. 2210-2218

[14] Halperin, D., Hu, W., Sheth, A., and Wetherall, D.: "Tool release: gathering 802.11 n traces with channel state information", *ACM SIGCOMM Computer Communication Review*, 2011, 41, (1), pp. 53-53

[15] Xiao, J., Wu, K., Yi, Y., Wang, L., and Ni, L.M.: "Pilot: Passive Device-Free Indoor Localization Using Channel State Information",in *Distributed Computing Systems (ICDCS), 2013 IEEE 33rd International Conference on,* 2013, pp. 236-245

[16] Jiang, X., Kaishun, W., Youwen, Y., Lu, W., and Ni, L.M.: "FIMD: Fine-grained Device-free Motion Detection",in *Parallel and Distributed Systems (ICPADS), 2012 IEEE 18th International Conference on,* 2012, pp. 229-235

[17] Zimu, Z., Zheng, Y., Chenshu, W., Longfei, S., and Yunhao, L.: "Omnidirectional Coverage for Device-free Passive Human Detection", *Parallel and Distributed Systems, IEEE Transactions on*, 2014, 25, (7), pp. 1819-1829

[18] Kun, Q., Chenshu, W., Zheng, Y., Yunhao, L., and Zimu, Z.: "PADS: Passive detection of moving targets with dynamic speed using PHY layer information",in *Parallel and Distributed Systems (ICPADS), 2014 20th IEEE International Conference on,* 2014, pp. 1-8

[19] Gong, L., Yang, W., Man, D., Dong, G., Yu, M., and Lv, J.: "WiFi-Based Real-Time Calibration-Free Passive Human Motion Detection", *Sensors*, 2015, 15, (12), pp. 29896

[20] Yang, Z., Zhou, Z., and Liu, Y.: "From RSSI to CSI: Indoor localization via channel response", *ACM Comput. Surv.*, 2013, 46, (2), pp. 1-32