2012 IEEE 18th International Conference on Parallel and Distributed Systems

FIMD: Fine-grained Device-free Motion Detection

Jiang Xiao, Kaishun Wu*, Youwen Yi, Lu Wang and Lionel M. Ni
Department of Computer Science and Engineering, Guangzhou HKUST Fok Ying Tung Research Institue,
The Hong Kong University of Science and Technology
*Corresponding Author
Email: {jxiao, kwinson, ywyi, wanglu, ni}@cse.ust.hk

***Abstract*—Device-free passive (Dfp) motion detection seeks to monitor the position change of entities without actively carrying any physical devices. Recently, WLAN with a rich set of installed wireless infrastructures enables motion detection in the area of interest. WLAN-enabled DfP motion detection rely on received signal strength (RSS) is verified to be able to provide acceptable high accuracy. Although RSS can be easily measured with commercial equipments, it is suspectable to measurement itself due to multipath effect in indoor environment. In this paper, we present an Indoor device-free Motion Detection system (FIMD) to overcome the preceding RSS-based limitation. FIMD explores properties of Channel State Information (CSI) from PHY layer in OFDM system. FIMD is designed based on the insight that CSI maintains temporal stability in static environment, while exhibits burst patterns when motion takes place. Motivated by this observation, FIMD uses a novel feature extracted from CSI to leverage its temporal stability and frequency diversity. The motion detection is conducted with outliers identification from normal features in continuous monitoring using density-based DBSCAN algorithm. Moreover, we leverage two schemes including false alert filter and data fusion to enhance the detection accuracy.**

We implement FIMD system with commercial IEEE 802.11n NICs and evaluate its performance in two typical indoor scenarios. Experiment results show that FIMD can achieve high detection rate. Moreover, comparing with RSSI, the feature extracted from CSI enables better detection performance in accuracy and robustness to narrowband interference.

***Index Terms*—PHY, CSI, WLAN, Motion Detection**

I. Introduction

Motion detection is a fundamental process of detecting whether there exists any entity moving around the area of interest. It is an essential primitive that is increasingly needed by a wide range of applications in wireless/mobile computing. For instance, hospitals can monitor the status of patients and release a health care alarm whenever the patient is in a paroxysm of disease, the military can investigate the invasion of enemies for frontier defence, and companies and residence communities can surveillance anomalous intrusion for safety precautions, etc. Although there exist several motion detection systems, they have some inherent limitations. Device-based motion detection is ubiquitously adopted in many works, but it requires specialized hardware like accelerometer, radar-sensor and photo-sensor, which is fairly unprofitable for large deployments or useless under some conditions. Ideally, an appropriate motion detection system should be able to provide high detection accuracy, low latency, while can be spread scalable. To this end, the concept of device-free motion detection is proposed and developed with growing interest.

Recently, a worldwide convergence of wireless LANs (WLAN) has occured for ease of installation and open access. The popularity of WLAN has opened up a chance for research community to develop device-free passive (Dfp) motion detection systems with well established WLAN infrastructure [2]. Radio signal strength (RSS), which is a coarse measurement of the received power, has been widely applied for Dfp motion detection in WLAN [8], [9], [4], [10]. In these WLAN-based Dfp motion detection systems, researchers utilize the existing access points (APs) to capture and process RSS when received a packet. They explore the motion-dependent characteristic of RSS for indicating the motion behavior. This is due to the fact that RSS will become anomalous when the environment changes. Even though the prior RSS-based techniques have made significant progress, they still suffer from the following main problem: RSS is known to be of high variability as susceptible to the measurement itself. As a result, slow dynamic is easily hidden by the inherent RSS variance, which leads to miss detection.

Driven by the necessity of robust Dfp motion detection systems, we argue that a reliable metric to overcome the above challenges is in need. Such metric should meet two requirements: first, it should provide the capability to resist from the narrowband interference in the 2.4GHz band; second, it should be temporal stable in static environment while sensitive enough to a motion instantly. Fortunately, we gain an opportunity to obtain such metric with the advance of endorsement of Orthogonal Frequency Division Multiplexing (OFDM) technique in the leading WLAN standards. Based on OFDM system where data are modulated on multiple frequency-independent subcarriers and transmitted simultaneously, channel measurement at the subcarrier level becomes available. Such channel properties over all the subcarriers in frequency domain can be represented by Channel State Information (CSI) from PHY layer. Compared to RSS, CSI has two advantages: first, CSI will only be influenced by several subcarriers thanks to frequency diversity property [14], [15]. Second, unlike collecting RSS sequentially over time series, CSI of multiple frequencies can be obtained at one time. CSI value stays fairly stable over time in a static environment [14], [15], which outperforms the spontaneous high variable RSS. Third, CSI is independent of AP power adjustment instead of susceptible RSS. Therefore, these three properties make CSI a promising measurement to investigate for WLAN-based device-free motion detection system.

1521-9097/12 $26.00 © 2012 IEEE
DOI 10.1109/ICPADS.2012.40

In this paper, we propose a novel metric based on CSI inherent to IEEE 802.11n to address the device-free motion detection problem. We present the design of a Fine-grained Indoor Motion Detection (FIMD) system that provides high accuracy. To achieve this, we first use commercial 802.11n NICs to collect CSI samples by Detecting Points (DPs) fixed in the area of interest. Next, a maximum eigenvalue-based approach is proposed to extract the feature appropriate for representing different signal patterns, i.e., static and dynamic. Afterwards, we use the DBSCAN [7] algorithm to classify the feature values and monitor the "burst" behavior over a single RF link. Finally, we apply a simple windowing filter technique to reduce the false alarm rate.

The key contributions in FIMD are summarized as follows.

1) We propose to use the fine-grained PHY layer information CSI for motion detection and, to the best of our knowledge, present the first description of why CSI is more beneficial than traditional RSS-based approach in WLAN: CSI is estimated with high accuracy, and exhibit better temporal accuracy.
2) We present the design and implementation of our system, showing how to exact the feature value based on CSI by leveraging its temporal stability and frequency diversity and use it for motion detection.
3) We implement the FIMD system in commercial IEEE 802.11 NICs. Evaluation results from real world experiments demonstrate that the CSI-based motion detection provided by FIMD can improve the detection accuracy while reduce the false alarm rate, and outperform the corresponding traditional RSSI-based RASID system.

The rest of this paper is organized as follows. In Section II, we present the existing work on motion detection in two categories of techniques: device-based and device-free. Section III presents the architecture of the FIMD system. This is followed by the methodology of the CSI-based DfP motion detection in Section IV. In Section V, we introduce the implementation of FIMD and evaluate its performance on different scale environments and provide a comparison to RSS-based RASID system. Finally, we render our conclusions and suggestions are made for future research in Section VI .

II. Related Work

Massive researches have been done in the area of motion detection in the context of pervasive and mobile computing. In general, it can be broadly classified as device-based and device-free techniques.

Device-based techniques. Most approaches require the entities to carry on special hardwares to achieve motion detection capability, such as accelerometers, pressure sensors, Infrared sensors, video cameras, etc. Nevertheless, the limitation of wireless sensors [11] lies in the high cost and the camera will loss function due to condition constrain. Alternatively, Wallbaum et al. [8] employ radio signal strength (RSS) using already installed WLAN infrastructure. Another flavor of WLAN-based motion detection systems rely on temporal channel response [1]. The authors propose to leverage temporal channel response as a link signature between the transmitter and receiver. With the knowledge of link signature variance, a moving event of the transmitter can be detected [5], [6]. However, these techniques are improper for ubiquitous scale setting due to high cost or large deployment overhead. Further, while they still require effort in terms of carrying on device at the transmitter, our FIMD system is completely device-free.

Device-free techniques. Researchers propose a novel concept of Device-free [2], also known as Transceiver-free [12] techniques. It explores a variety of technologies to bypass the device-based constraint, such as computer vision [16], wireless sensors [12] and RFID tags [13], [9]. The main drawbacks of these work lie in the need of special devices compensating for the detection functionalities. In [2], the authors alternatively exploit to leverage WLAN-based technique to reduce the hardware efforts since the entity itself does not carry on any wireless device. They discuss the challenges of Device-free techniques and propose two feature extraction algorithms including moving average (MA) and moving variance (MV) for motion detection. [3] applies Maximum Likelihood Estimator (MLE) algorithm to enhance the performance of the DfP system in real environments. Recently, RSS-based RASID system [4] further improve the detection accuracy by analyzing the RSS features and adopting a nonparametric technique for adapting to environment changes. In this paper, we introduce the use of a new metric CSI from PHY layer for motion detection, which can be sensitive to environment changes and resist to temporal variance.

III. Architecture

In this section, we present the architecture of FIMD along with design challenges.

FIMD ia a system that exploits the suitable features of CSI from commercial NICs to provide motion detection. In general, narrowband interference at 2.4 GHz is unavoidable in a monitored area of indoor setting. Therefore, in the presence of narrowband interference, how to extract suitable features from CSI for distinguishing signal patterns in static/dynamic environments is the first challenge we need to overcome. Channel State Information (CSI) is information that estimates the channel by representing the channel properties of a communication link. More specifically, CSI exploits the channel status when a RF signal propagates over multiple subcarriers. Intuitively, CSI will exhibit different features under static/dynamic environments. Even that CSI can differentially represent the normal/dynamic patterns, there may still exist false detection. For example, the false alarm rate will arise due to the increasing huge volume of input data. Moreover, the presence of noise under the combined effect of, for instance, scattering, fading, and power decay with distance in collected CSI samples may lead to miss detection. The second challenge we need to undertake is how to accurately detect a motion event with minimized erroneous. Besides, from the perspective of communication efficiency, APs will adapt the transmission

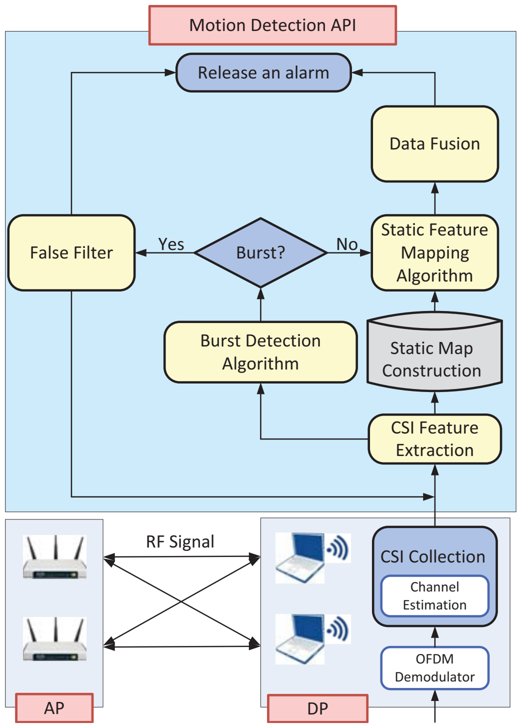

Fig. 1: System Architecture.

power in order to maximum the throughput. However, RSS-based approach suffers from this power adjustment and causes degrading detection accuracy. How to maintain the detection capacity under adjustment condition remains a third challenge in our work.

We first describe the overall vision of FIMD as shown in Fig. 1. FIMD consists of three functional components: access points (APs), detecting points (DPs), and FIMD server. The APs will send out beacon messages over radio frequency (RF) link. The DPs support the CSI collection functionality by transmitting RF signal. FIMD server then complete the whole detection process online. The APs and DPs are positioned in the area of interest and kept stationary during the whole detection period. In our setting, there are serveral pairs of APs and DPs, each equipped with multiple antennas. Based on the current IEEE 802.11n standards, no additional hardware requirement on both APs and DPs. Upon periodically receiving the OFDM beacon message from APs, DPs will first collect the raw CSI value in the channel estimation block. Specifically, let x be the transmitted vectors at APs, y be corresponding received vectors at DPs, respectively. Then fine-grained CSI - channel gain across all subcarriers at the PHY layer - can be estimated as follows:

$$\hat{H} = \frac{y}{x}. \tag{1}$$

After that, FIMD server will import the CSI measurement collected by the DPs and start the detection functionality. There exists five important modules operating on the server, including: CSI Feature Extraction, Burst Detection, Static Map Construction, False Alert Filter, and Data Fusion. In the designated CSI Feature Extraction module, raw CSI generated from 30 groups different subcarriers will be first processed. Intuitively, channel status information CSI will exhibit differential characteristics in static and dynamic environments. We conduct preliminary experiments in typical indoor scenarios to validate this intuition. We succeed in exploiting the characteristic of CSI which reveals normal and motion behavior in diverse ways. A maximum eigenvalue over sliding window is used to represent the feature value corresponding to normal or motion behavior. Next, the Burst Detection module runs on the processed CSI-based feature value dataset over multiple pairs of links independently. For burst detection, the link status is analyzed using a density-based DBSCAN classification algorithm. The algorithm will examine the feature value in the dataset of each link to produce clusters. If the points in a dataset belongs to a single cluster, the relevant status is deemed to be static. In contrast, if there exists more than one cluster in the particular dataset, it should be a dynamic status due to motion behavior. Since there may exist false detection, further analysis should be done to enhance the overall detection performance. According to the initial obtained results from Burst Detection, we generate two cases refinement: 1)False Alarm Filter: using a simple windowing algorithm, we can filter out the false detection that erroneously generate a burst alarm when no motion appears; 2)Data Fusion: even when no burst has been detected during the initial burst detection phase, there may exist some missing cases. Therefore, we enhance the detection accuracy by adding this Data Fusion module and update the static feature of processed CSI. In what follows, we will detail this proposed framework in a divide-and-conquer manner.

IV. Methodology

In this section, we describe the design terminology of FIMD. The methodology of this CSI-based motion detection approach can be broken down into five parts according to the corresponding modules introduced in previous section III.

A. CSI Feature Extraction

According to our modification of chipset firmware, the raw CSIs are divided into 30 groups each with 2 subcarriers. The $N = 30$ groups CSI values can be expressed as

$$\mathrm{H} = [H_1, H_2, \cdots, H_i, \cdots, H_N]^T, \ i \in [1, 30], \tag{2}$$

where each subcarrier H_i is defined as

$$H_i = |H_i| e^{j \sin\{\angle H_i\}}, \tag{3}$$

where $|H_i|$ is the amplitude response and $\angle H$ is the phase response of the i_{th} subcarrier.

The first main module - CSI Feature Extraction serves as a prerequisite of the following modules. The core idea of this module is to process the 30 group CSIs data received from multiple DPs, and explore the characteristics of CSI that distingush the signal patterns under static or dynamic environemnts.

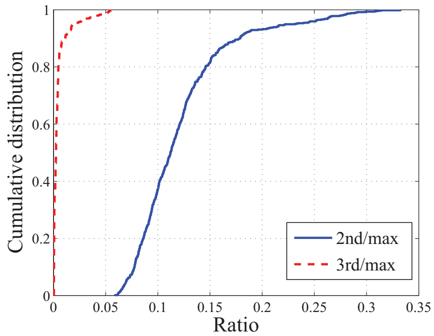

Fig. 2: CSI Feature Extraction

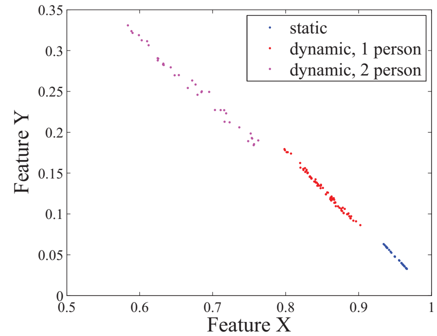

Fig. 3: CSI Features in Static/Dynamic Environments

Specifically, we tend to differeniate the CSI dynamic pattern from CSI stationary pattern due to the movement of entities.

To this end, we first process continuous CSIs starting from H_k over a sliding window W. Given a sliding window W with length n, CSIs can be expressed as

$$\mathbb{H} = [\mathrm{H}_k, \mathrm{H}_{k+1}, \cdots, \mathrm{H}_{k+n}], \tag{4}$$

Next, we need to identify the properties of CSI that reflects static/dynamic signal patterns. In order to obtain the correlation factor between each column of $\mathbb{H}$, we generate a n-by-n square matrix $\mathbf{C}$ over the n sequential packets as

$$\mathbf{C} = \begin{bmatrix} \mathrm{C}(i,i) & \cdots & \mathrm{C}(i,i+n) \\ \vdots & \ddots & \vdots \\ \mathrm{C}(i+n,i) & \cdots & \mathrm{C}(i+n,i+n) \end{bmatrix} \tag{5}$$

where each element $\mathrm{C}(i,j)$ in the matrix $\mathbf{C}$ is the correlation ratio between the H_i and H_j as

$$\mathrm{C}(i,j) = corr(\mathrm{H_i}, \mathrm{H_j}) \tag{6}$$

The value of diagonal entries in matrix $\mathbf{C}$ is equaled to 1. In our method, we multiply a scaler λ to obtain the eigenvector $\mathbf{eigen}$ of matrix $\mathbf{C}$. Thus, the CSI feature extraction problem is equivalent to finding the maximum eigenvalue of this eigenvector after normalization. The feature value associated with CSI is defined as $\mathbf{V}$,

$$\mathrm{V} = max(\mathrm{eigen(C)/n}) \tag{7}$$

where n is the sliding window length that constraints the column number of matrix $\mathbf{C}$.

If all the eigenvalue of each column are the same as 1, the corresponding maximum $\mathrm{eigen(C)}$ equals to 1 while the rest are 0. Therefore, with higher correlation ratio between each column in H, the signal will exhibit more likely to be static. Reversely, if the eigenvalue suddenly decrease to a small value, the lower correlation may indicate an occurrence of motion. We conducted preliminary experiments for validating the proposed feature extraction approach. Typically, the maximum and second maximum eigenvalues are large while from the third one, the eigenvalue becomes small and are considered negligible as shown in Fig. 2. We plot the maximum and second maximum eigenvalues denoted as $feature\ x$ (x-axis) and $feature\ y$ (y-axis) on a 2-dimensional Fig. 3, respectively. There are three main observations from the figure: 1)the eigenvalue in static status is maximum and approaching to 1; 2)the eigenvalue will become smaller in the dynamic environments; 3)if more people presented in the region of interest, the eigenvalue will further decrease due to higher variance.

Obtained from CSI-based correlation matrix $\mathbf{C}$, eigenvalue $\mathbf{V}$ is selected to be feature lying on two notable benefits. First, such eigenvalue $\mathbf{V}$ is independent with power control. RSS-based approach is known to be susceptible to transmitted power at the APs, and thus requires additional APs complement. Alternatively, CSI-based eigenvalue relies on correlation over multiple groups CSIs and irrelevant to power changing. Second, this feature value is robust to narrowband interference at 2.4 GHz.

B. Static Profile Construction

FIMD's Static Profile Construction module represents the stationary signal patterns in the monitored area. In our FIMD system, this is an optional module only if off-line training is available and necessary. It should be noted that we will not use this module in our clustering based detection, but for the comparison with RSS, this module is used in the RASID-like approach.

Conceptually similar to recent work [4] that uses non-parametric kernel density estimation of RSS value over time, we then propose to leverage the more temporal stable metric CSI and construct a static feature profile. In general, the construction process is supposed to explore the frequency diversity of CSI that represents the prominent static pattern frequencies over multiple subcarriers. Therefore, instead of using the coarse RSS defined in the estimated density function [4], this module inputs the stationary CSI-based feature values generated from the Feature Extraction Module.

C. Burst Detection

The key module of our FIMD system is Burst Detection, which plays an important role in the detection process. It monitors the occurrences of CSI variance due to motion events

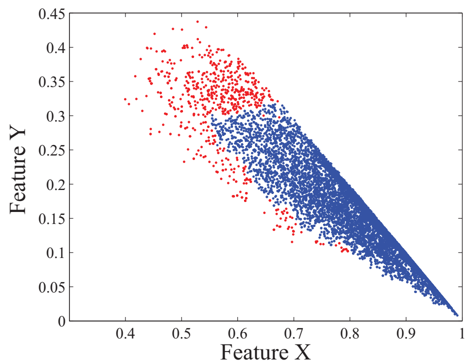

Fig. 4: DBSCAN Clustering Results

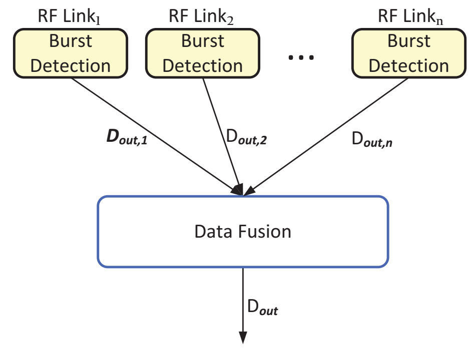

Fig. 5: Data Fusion over Multiple RF Links

during our measurement period. In particular, Burst Detection views motion detection as a pattern recognition problem, rather than a signature matching problem. It relies on the fact that the patterns of motion events are necessarily anomalous, and deviate from the static ones. Such that the burst CSI patterns is deemed a possible motion action. Therefore, we need an effective algorithm to classify the CSI patterns and determine the "burst" motion occurrence. Density-bsed classification algorithm DBSACN [7] is a good fit for Burst Detection based on two favorable features: (1)no priori knowledge of the numbers of clusters is required (2)discovery of clusters with arbitrary shape.

There are two input parameters in our algorithm including

- ε (eps) - the radius that delimitate the neighborhood area of a point, denoted as $N(p)$
- $minPts$ - minimum number of points that must exist in the ε-neighborhood points,

The key idea of the DBSCAN clustering algorithm is that, for each point in a cluster, ε-neighborhood has to contain at least more than the $minPts$. That is, the density in the ε-neighborhood has to exceed some predefined threshold. Given a specific CSI-based feature value dataset of a RF link between AP and DP, the DBSCAN clustering algorithm obeys the following principles:

- **Principle 1**: Each cluster contains at least one feature value V_i as core point p that the size of $N(p)$ is at least $minPts$.
- **Principle 2**: Given any two feature values V_1 and V_2 with size of ε-neighborhood greater than $minPts$, then V_1 and V_2 are in the same cluster.
- **Principle 3**: If feature value V_i has size of ε-neighborhood less than $minPts$, and no core point is contained in $N(p)$, then V_i is an outlier.

In order to discuss whether a set of points is similar enough to be considered a cluster, we need a distance measure $Dist(V_i, Vj)$ which tells how far points V_i and V_j are. In our algorithm, we apply Euclidian formula to measure $Dist(V_i, Vj)$ as follows:

$$\mathrm{Dist(V_i, Vj)} = \sqrt{|x_{V_i} - x_{V_j}|^2 - |y_{V_i} - y_{V_j}|^2} \tag{8}$$

Therefore, if the number of feature values assigned to a particular cluster within a sliding window is greater than a threshold η, the state is deemed to be static. Otherwise, it is classified as a "Burst" state. Fig. 4 serves as an example to show how DBSCAN is able to detect the motion event of incoming feature value dataset. As mentioned in Sec. IV-A, we generate the maximum eigenvalue and the second maximum eigenvalue as feature values. We associate each feature value as a point on a 2-dimensional density figure, and the results of the cluster analysis in static/dynammic are shown in Fig. 4.

As previously stated, detection accuracy is the primary design goal of FIMD system, we need to minimize the errors that potentially happened in the whole detection procedure. So we further perform two classes of schemes over the Burst Detection results to resolve the false alarm and miss detection as follows:

D. *False Alarm Filter*

From the perspective of improving detection ability, a simple Burst Detection may be insufficient. Instead, a specific scheme to suppress the false alarm before generating a detection alert is in need. Here, we choose to apply a simple windowing technique.

Observed from the empirical study, a single motion instance always lasts a short period when receiving continuous packets. Such that the dynamic pattern can be determined from CSI-based feature value over a specific sliding window W, as well from the ones immediately to the left and right of W. Based on the windowing filter, we shift the window to the left neighbor and right neighbor and compute the corresponding feature value. If the feature value in window is isolated from the adjacent ones, then the "burst" instance generated from Burst Detection module can be determined as a false detection and filtered out.

E. *Data Fusion*

Another source of erroneous detection is known to be miss detection. That is, for miss detection, we perform additional steps to decrease the miss detection as few as possible.

Previously, each single RF link generates an initial detection results based on Burst Detection algorithm, which the output is

Fig. 6: Testbed 1: Research Laboratory

Fig. 7: Testbed 2: Corridor

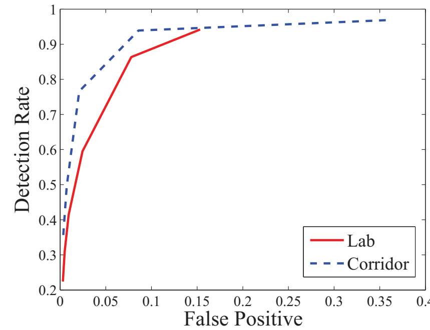

Fig. 8: ROC in Two Testbeds

classified into either normal static or anomaly dynamic. Missed Filter takes advantage of data fusion technique over multi-link CSIs, which synergistically integrating the CSIs from multiple links to produce comprehensive information about a detection event. This results in a reduced false negative detection rate over single-link approach. Fig. 5 shows multiple RF links contributing their decisions whether a motion has taken place or not to a fuser.

First, the output decision of Burst Detection module is defined as D. Each $D_{out,i}$ of a single RF link will then be submitted to the Data Fusion block.

$$\mathrm{D} = \begin{cases} 1, dynamic\ ; \\ 0, static\ . \end{cases} \tag{9}$$

The output of Data Fusion block D_{out} is given by

$$\mathrm{D_{out}} = \frac{P(D_1, D_2, \ldots, D_n | D = 1)}{P(D_1, D_2, \ldots, D_n | D = 0)} \tag{10}$$

where $P(D_1, D_2, \ldots, D_n | D = 1)$ is the probability of each Burst Detection output D_i if motion is known to occur. Likewise, $P(D_1, D_2, \ldots, D_n | D = 0)$ is the probability of output D_i over a single RF link if the detection process is in stationary. Therefore, Equation 10 is the likelihood ratio of an overall burst detection.

V. Performance Evaluation

We divide the evaluation section into two parts: first, we evaluate the performance of FIMD in two different indoor scenarios; second, we compare the feature obtained from CSI with that based on RSS on the RASID system [4].

A. Experimental Setting

As described in the previous section III, FIMD is implemented in three main parts: APs, DPs and detection sever. In our experiments, we use the TL-WR941ND router with three antennas as AP, which runs on different channel. A HP laptop equipped with a three-antenna Intel WiFi Link 5300 (iwl5300) IEEE 802.11n NICs is used for DP. In our experiments, we only use the first antenna and the enhancement with multiple antennas is left for our future work. During the detection period, APs will send out beacon messages to DPs. DPs gather these messages along with CSIs and upload them to detection server for processing.

We conduct experiments under two typical indoor scenarios as follows:

1) **Research Laboratory** First, we set up a testbed in a $7m \times 11m$ research laboratory in Hong Kong University of Science and Technology as shown in Fig. 6. The AP was placed on the top of the shelters. At the DP side, the CSI values were collected continuously in both static and dynamic environments. In particular, DP gathered the raw CSI of packages per minute in a format as described in Section III and the total time cost on data collection is two hours. For the purpose of motion detection, we generated two test sets covering the entire area of the laboratory including a static set and a motion set. The motion set is formed by an individual walking back and forth around the region of interest with nonstop. Simultaneously, the counterpart RSS values were recorded for comparison.
2) **Corridor** Second, we performed experiments in an environment with multiple offices aside in our academic building, which is a long and narrow corridor with $32.5m \times 1.5m$ space. In this scenario, there is 1 pair of AP and DP that placed in a fixed position as shown in Fig. 7. We also collected same amount of CSIs over transmission link and uploaded to FIMD server. For each link, we recorded RSS samples for both performance comparison in Section V.

B. Performance Evaluation

1) Evaluation Metric: We set up the following metric to access the performance of the proposed FIMD system:

- True Positive (TP) Rate: TP rate refers to the probability that a motion event is properly detected.

2) Experimental Results: First, we depict a Receiver Operating Characteristic (ROC) curve that graphically interpret the detection performance in the presence of false alarm. ROC curve can explicitly show the tradeoff between the FP rate (X-axis)and TP rate (Y-axis). Here, we use DR to represent the TP rate, which measures the effecitveness of the FIMD

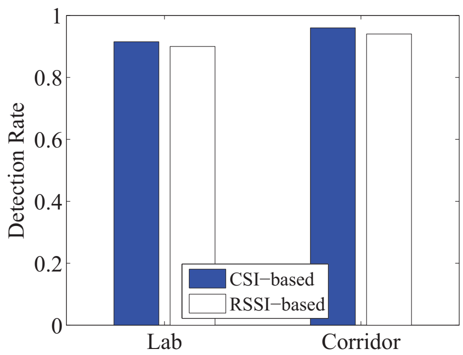

Fig. 9: CSI-based Feature vs. RSS-based Feature

system according to the following Equ. 11,

$$DR = \frac{TP}{(TP + FN)} \times 100\% \tag{11}$$

Fig. 8 presents the MDR rate with respect to false alarm rate in two testbeds. In Lab, for a FP rate less than or equal to 1% the detection rate would be greater than 70%, and for a FP rate greater than 14% the detection rate would be greater than 90%. Likewise, the ROC curve in Corridor shows that detection rate would be greater than 90% when FP rate is around 9%.

3) Comparison with RSS-based: So far, we have been focusing on the performance of the proposed CSI-based FIMD system. To study the beneficial gain of CSI-based feature over RSS-based feature, we compare it against the most relevant RSS-based motion detection system RASID. RASID is a well known RSS-based Device-free passive detection system which consists of an offline training phase and an online monitoring phase. It leverages standard deviation (SD) of RSS as the feature approximates it distribution with a kernel function. For a fair comparison, we keep the whole RASID detection process and only replace the RSS-based feature with proposed CSI-based feature. Where only the maximum eigenvalue extracted from CSI correlation over a sliding window. We implement RASID on FIMD server in both testbeds and set the sliding window length to be 10 as shown in Fig. 9. The length of update window is fixed to be 30. From Fig. 9, we can observe that CSI-based feature slightly outperforms the RSS-based one for the purpose of motion detection due to better temporal stability. In summary, CSI-based feature can provide better detection performance comparing with the counterpart based on RSSI.

VI. Conclusions and Future Work

A novel device-free indoor motion detection FIMD system that uses existing WLAN infrastructure is presented in this paper. For the first time, we propose to leverage the characteristics of fine-grained CSI from PHY layer for distinguishing static/dynamic environments in the indoor area of interest. We first exploit such feature using CSI Feature Extraction module and then utilize the DBSCAN algorithm in Burst Detection module to monitor the motion behavior. After that, we apply one scheme to reduce the false alarm rate. We have implemented FIMD with commercial IEEE 802.11n NICs and compared it against traditional RSS-based RASID system. Using empirical testbed evaluation, we show that CSI-based motion detection is feasible and outperforms the RSS-based RASID system. Based on deployment in two different scenarios, performance evaluation results show that FIMD can achieve sufficient accuracy with the proposed CSI-based feature.

In next stage, we plan to extend FIMD to distinguish different kinds of motions.

Acknowledgment

This research was supported in part by 2012 Guangzhou Pearl River New Star Technology Training Project (No.2012J2200081), Guangdong NSF Grant (No. S2012010010427), Hong Kong RGC Grants HKUST617811 and HKUST617212, China NSFC Grants 61202454, 61027009 and 60933011, and Science and Technology Planning Project of Guangdong Province, China, under Grant No. 2011A011302001.

References

[1] N. Patwari,"Robust Location Distinction using Temporal Link Signatures," in *Proc. of ACM MobiCom*, 2007.

[2] M. Youssef, M. Mah, A. Agrawala,"Challenges: Device-free Passive Localization for Wireless Environments," in *Proc. of ACM MobiCom*, 2007.

[3] M. Moussa and M. Youssef,"Smart Devices for Smart Environments: Device-free Passive Detection in Real Environments," in *Proc. of IEEE PerCom Workshops*, 2009.

[4] A.E. Kosba, A. Saeed, M. Youssef,"RASID: A Robust WLAN Device-free Passive Motion Detection System," in *Proc. of IEEE PerCom*, 2012.

[5] J. Zhang, M.H. Firooz, N. Patwari, S.K. Kasera,"Advancing Wireless Link Signatures for Location Distinction," in *Proc. of ACM MobiCom*, 2008.

[6] J. Zhang, S.K. Kasera, N. Patwari, P. Rai,"Distinguishing Locations Across Perimeters Using Wireless Link Measurements," in *Proc. of IEEE INFOCOM*, 2011.

[7] M. Ester, H.P. Kriegel, J. Sander, X. Xu, "A density-based algorithm for discovering clusters in large spatial databases with noise," in *Proc. of the Second International Conference on Knowledge Discovery and Data Mining (KDD)*, 1996.

[8] M. Wallbaum, S. Diepolder,"A Motion Detection Scheme For Wireless LAN Stations," in *Proc. of ICMU*, 2006.

[9] R. S. Moore, R. Howard, P. Kuksa, and R. P.Martin, "A Geometric Approach to Device-Free Motion Localization Using Signal Strength," in *Technical Report, Rutgers University*, 2010.

[10] J. Yang, Y. Ge, H. Xiong, Y.Y. Chen, and H.B. Liu, "Performing joint learning for passive intrusion detection in pervasive wireless environments," in *Proc. of IEEE INFOCOM*, 2010.

[11] D.J. Kim, B. Prabhakaran, "Motion fault detection and isolation in Body Sensor Networks," in *Proc. of IEEE PerCom*, 2011.

[12] D. Zhang, J. Ma, Q. Chen, and L.M. Ni,"An RF-Based System for Tracking Transceiver-Free Objects," in *Proc. of IEEE PerCom*, 2007.

[13] D. Zhang, Y.H. Liu, L.M. Ni,"RASS: A real-time, accurate and scalable system for tracking transceiver-free objects," in *Proc. of IEEE PerCom*, 2011.

[14] A. Bhartia, Y. Chen, S. Rallapalli, and L. Qiu, "Harnessing Frequency Diversity in Wi-Fi Networks," in *Proc. of ACM MobiCom*, 2011.

[15] K. Wu, J. Xiao, Y. Yi, and Lionel M. Ni, "FILA: Fine-grained Indoor Localization," in *Proc. of IEEE INFOCOM*, 2012.

[16] J. Krumm, L. Williams, and G. Smith, "SmartMoveX on a Graph - An Inexpensive Active Badge Tracker," in *Proc. of UbiComp*, 2002.