TRIEDS: Wireless Events Detection Through the Wall

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***Abstract*—In this paper, we propose a novel wireless indoor events detection system, TRIEDS. By leveraging the time-reversal technique to capture the changes of channel state information (CSI) in the indoor environment, TRIEDS enables low-complexity single-antenna devices that operate in the ISM band to perform through-the-wall indoor multiple events detection. The multipath phenomenon denotes that the electromagnetic signals undergo different reflecting and scattering paths in a rich-scattering environment. In TRIEDS, each indoor event is detected by matching the instantaneous CSI to a multipath profile in a training database. To validate the feasibility of TRIEDS and to evaluate the performance, we build a prototype that works on ISM band with carrier frequency being 5.4 GHz and 125 MHz bandwidth. Experiments are conducted to detect the states of the indoor wooden doors. Experimental results show that with a single receiver access point and transmitter (client), TRIEDS can achieve a detection rate higher than 96.92% and a false alarm rate smaller than 3.08% under either line-of-sight (LOS) or non-LOS transmission.**

***Index Terms*—Indoor events detection, spatial–temporal resonance, through the wall, time reversal (TR), wireless events detection.**

I. Introduction

The past few decades have witnessed the increase in the demand of surveillance systems which aims to capture and to identify unauthorized individuals and events. With the development of technologies, traditional outdoor surveillance systems become more compact and of low cost. In order to guarantee the security in offices and residences, indoor monitoring systems are now ubiquitous and their demand is rising both in quality and quantity. For example, they can be designed to guard empty houses and to alarm when break-in happens.

Currently, most indoor monitor systems basically rely on video recording and require cameras deployments in target areas. Techniques in computer vision and image processing are applied on the captured videos to extract information for real time detection and analysis [1]–[4]. However, conventional vision-based indoor monitor systems have many limitations. They cannot be installed in places requiring high level of privacy like restrooms or fitting rooms. Owing to the prevalence of malicious softwares on the Internet, vision-based indoor surveillance systems may lead to more dangers than protections, contradicting their intention. Moreover, vision-based approaches have a fundamental requirement of a line-of-sight (LOS) environment with enough illumination is indispensable.

On the other hand, sensing with the wireless signals to detect indoor events has gained a lot of attention [5]. By utilizing the fact that the received radio frequency (RF) signals can be altered by the propagation environment, device-free indoor sensing systems are capable of capturing activities in the environment through the changes in received RF signals. Common features of RF signals to identify variations during signal transmission for indoor events detection include the received signal strength (RSS) and channel state information (CSI). Due to its susceptibility to the environmental changes, the RSS indicator (RSSI) has been applied to indicate and further recognize indoor activities [6]–[9]. Sigg *et al.* [7] proposed a method that links the patterns of RSSI fluctuation to different human activities. An approach where the direction of human movement (HM) was determined according to the RSSI degradation among different receivers was proposed in [8]. Recently, an RSSI-based gesture recognition system was built where seven gestures were identified with accuracy 56% [9]. Furthermore, CSI information, including the amplitude and the phase, is now accessible in many commercial devices and has been used for indoor event detection [10]–[16]. In [10], the first two largest eigenvalues of CSI correlation matrix were viewed as features to determine whether environment is static or dynamic. Adib and Katabi [11] applied MIMO interference nulling technique to eliminate reflections off static objects and focus on a moving target, and used beam steering and smoothed MUSIC algorithm to extract the angle information of target. Han *et al.* [12] treated the CSI in the 3×3 MIMO system independently and the standard deviations of the CSI were combined with SVM for human activity detection. In [13], in order to locate the client with a fixed access point (AP), both the amplitudes of the CSI and the frequency diversity in OFDM spectrum were used to build a model for calculating the distance between the AP and the client. In [14], the histograms of the

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CSI amplitudes were utilized to distinguish between different human activities. In [15], a coarse relationship between variation in CSI amplitudes and the number of persons present was established. Wang *et al.* [16] proposed the CARM that leveraged the CSI-speed and CSI-activity models for detection. Moreover, a lip reading system based on WiFi signals was developed where the features of mouth motions were extracted through the discrete wavelet packet decomposition on CSI's amplitudes and classified with the help of dynamic time wrapping [17]. However, most aforementioned CSI-based indoor sensing systems rely on only the amplitudes of the CSI, whereas the phase information is discarded regardless of how informative it is.

Another category of technologies in device-free indoor monitor systems is adopted from radar imaging technology to track targets [18]–[21]. The radar technique can identify the delays of subnanoseconds in the time-of-flight (ToF) of wireless signals through different paths, by using the ultra-wideband (UWB) sensing. Hence, radar-based systems are capable of separating the reflection from the moving object behind the walls against the reflections from walls or other static objects [18]. However, the UWB transmission is impractical in commercial indoor monitoring systems, because it requires specific hardwares for implementation. Recently, Adib *et al.* [19]–[21] proposed a new radar-based system to keep track of different ToFs of reflected signals by leveraging a specially designed frequency modulated carrier wave that sweeps over different carrier frequencies. However, their techniques consume over 1 GHz bandwidth to sense the environment and only the images of result are obtained from the sensors, which requires further effort to detect the types of indoor events.

The aforementioned device-free systems have limitations in that they either require multiple antennas and dedicated sensors or require LOS transmission environment and UWB to capture features that can guarantee the accuracy of detection. In contrast, in this paper, we propose a time-reversal (TR)-based wireless indoor events detection system, TRIEDS, capable of through-the-wall indoor events detections with only one pair of single-antenna devices. In the wireless transmission, the multipath is the propagation phenomenon that the RF signals reaches the receiving antenna through two or more different paths. TR technique treats each path of the multipath channel in a rich scattering environment as a widely distributed virtual antenna and provides a high-resolution spatial–temporal resonance, commonly known as the focusing effect [22]. In physics, the TR spatial–temporal resonance can be viewed as the result of the resonance of electromagnetic (EM) field in response to the environment. When the propagation environment changes, the involved multipath signal varies correspondingly and consequently the spatial–temporal resonance also changes.

Taking use of the spatial–temporal resonance, a novel TR-based indoor localization approach, namely TRIPS, was recently proposed in [23]. By exploiting the unique location-specific characteristic of channel impulse response, TR creates a spatial–temporal resonance that focuses the energy of the transmitted signal only on the intended location. The TRIPS mapped the real physical location to the estimated CSI through the spatial–temporal resonance. The TR indoor locationing system was implemented on a WiFi platform, and the concatenated CSI from a total equivalent bandwidth of 1 GHz has been treated as the location-specific fingerprints [24]. Through nonline-of-sight (NLOS) experiments, the WiFi-based TR indoor locationing system achieved a perfect 5 cm precision with a single AP. TR-based indoor locationing system was an active localization system in that it required the object to be located to carry one of the transmitting or receiving device, such that the difference in the TR resonances between different locations of device is large.

Fig. 1. Prototype of TRIEDS.

Based on a similar principle as TRIPS, we utilize the TR technique to capture the variations in the multipath CSI due to different indoor events, and propose TRIEDS for indoor event detection. More specifically, thanks to the nature of TR that captures the variations in the CSI, maps different multipath profiles of indoor events into separate points in the TR space, and compresses the complex-valued features into a real-valued scalar called the spatial–temporal resonance strength, the proposed TRIEDS supports simplest detection and classification algorithms with a good performance. Compared with previous works on indoor monitoring systems which require multiple antennas, dedicated sensors, UWB transmission, or LOS environment, and rely on only the amplitude information in the CSI, TRIEDS introduces a novel and practical solution which can well support through-the-wall detection and only requires low-complexity single-antenna hardware operating in the ISM band. To demonstrate the capability of TRIEDS in detecting indoor events in real office environments, we build a prototype that operates at 5.4 GHz band with a bandwidth of 125 MHz, as shown in Fig. 1, and conduct extensive experiments in an office on the tenth floor of an sixteen-story building. During the experiments, we test the capability of TRIEDS of monitoring the states of multiple doors at different locations simultaneously. Using only one pair of single-antenna devices, TRIEDS could achieve perfect detection in LOS scenario and near 100% accuracy in detection when events happens in the absence of LOS path between the transmitter (TX) and the receiver (RX).

This paper is organized as follows. In Section II, the system overview for TRIEDS is briefly discussed and an introduction to TR technique is given. The details of how TRIEDS works are studied and analyzed in Section III, consisting of an offline training phase and an online testing phase. Moreover,

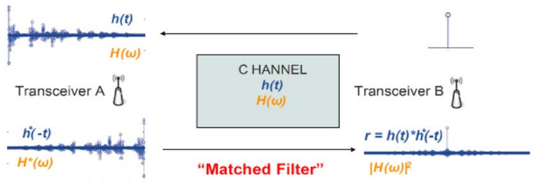


Fig. 2. TR-based wireless communication.

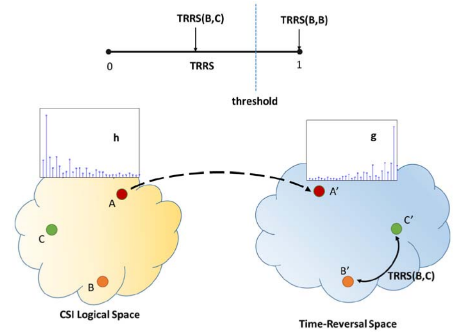


Fig. 3. Mapping between the CSI logical space and the TR space.

extensive experiments of TRIEDS in detecting indoor events in real office environments are conducted and the experimental results are investigated in Section IV. Based on the results in Section IV, we further discuss how the system parameters, human motions will affect the accuracy of TRIEDS, as well as the potential applications and future work. Finally, the conclusions are drawn in Section VI.

II. TRIEDS Overview

When an EM signal travels over the air in a rich-scattering indoor environment, it encounters reflectors and scatters that alter and attenuate signals differently. Consequently, the received signal at the receiving antenna is a combination of multiple altered copies of the same transmitted signal coming from different paths and suffering different delays. This phenomenon is well known as multipath propagation. In order to detect an indoor event, wireless sensors should be capable of tracking the targets against all other interferences. The previous indoor monitoring work can be categorized into two classes. The first class ignores the multipath effect and only uses a single-valued CSI feature like RSSIs for detection, which leads to the degradation of accuracy to some extent. On the other hand, the second class tries to separate different components in a multipath channel, by means of UWB transmission and specially designed modulated signals.

The previous work either views the multipath as the compromise to the system or separates the components in the multipath CSI by radar-based techniques. As opposed to them, TRIEDS is proposed as a novel system that monitors and detects different indoor events by utilizing TR technique. The details of TR technique are discussed as follows.

A. TR Technique

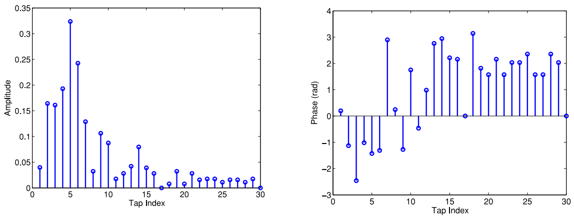
A typical TR wireless communication system is shown in Fig. 2 [25]. During the channel probing phase, the transceiver B sends an impulse to the transceiver A, which gets an estimated CSI $\mathbf{h}(t)$ for the multipath channel between A and B. Then, the corresponding TR signature is obtained by time-reversing and conjugating the estimated CSI $\mathbf{h}(t)$ as $\mathbf{g}(t) = \mathbf{h}^*(-t)$. During the second phase, the transceiver A transmits back $\mathbf{g}(t)$ and generates a spatial–temporal resonance at the transceiver B, by fully collecting and concentrating the energy of multipath channel. The TR spatial–temporal resonance can be viewed as the resonance of EM field in response to the environment, also known as the TR focusing effect [22].

As originally investigated in the phase compensation over telephone line [26], TR technique was then extended to the acoustics [27]. The spatial–temporal resonance of the TR has been proposed as theory and validated through experiments in both acoustic domain and RF domain [28]. In the RF domain, the property of TR spatial–temporal resonances of EM waves have been studied in [29] and [30]. Moreover, the TR technique relies on two assumptions, i.e., the channel reciprocity and the channel stationarity. The channel reciprocity demonstrates the phenomenon that the CSI for both the forward and the backward links is highly correlated, whereas the channel stationarity requires that the CSI remains highly correlated during a certain period. Both of the assumptions were validated in [23], [25], and [31], respectively.

In the indoor environment, there exists a large amount of propagation paths for EM signals due to the presence of scatters and reflectors. As long as the indoor propagation environment changes, the received multipath profile varies accordingly. As demonstrated in Fig. 3, each dot in the CSI logical space represents an indoor event or location, which is uniquely determined by the multipath profile $\mathbf{h}$. By taking a time-reverse and conjugate operation over the multipaths, the corresponding TR signatures $\mathbf{g}$ are generated and the points in the CSI logical space as marked by "A," "B," and "C" are mapped into the TR space as "A′," "B′," and "C′." In the TR space, the similarity between two indoor events or indoor locations is quantified by the strength of TR resonances. The definition of TR resonating strength (TRRS) is given in (3), where $\mathbf{h}_1$ and $\mathbf{h}_2$ represent the multipath profiles in the CSI logical space and $\mathbf{g}_2$ is the TR signature in the TR space. The higher the TRRS is, the more similar two points are in the TR space. Similar events defined by a threshold on TRRS will be treated as a single class in TRIEDS. Leveraging the TR technique, a centimeter-level accurate indoor locationing system, named as TRIPS, was proposed in [23]. In TRIPS, each of the indoor physical locations was mapped into a logical location in the TR space and can be easily separated and identified using TRRSs. Taking the advantage of the TR space to separate multipath profiles with small differences, TRIEDS is capable of monitoring and detecting different indoor events with a high accuracy.

III. System Model

In this part, we present a detailed introduction to the proposed TR-based indoor events detection system, TRIEDS. The proposed TRIEDS exploits the intrinsic property of TR technique that the spatial–temporal resonance fuses and



(a) (b)

Fig. 4. Example of indoor CSI. (a) Amplitude of CSI. (b) Phase of CSI.

compresses the information of the multipath propagation environment. To implement the indoor events detection based on the TR spatial–temporal resonances, TRIEDS consists of two phases: 1) the offline training and 2) the online testing. During the first phase, a training database is built by collecting the signature $\mathbf{g}$ of each indoor events through the TR channel probing phase. After training, in the second phase, TRIEDS estimates the instantaneous multipath CSI $\mathbf{h}$ for current state and makes the prediction according to the signatures in the offline training database by means of the strength of the generated spatial–temporal resonance. The detailed operations are discussed in the followings.

A. Phase 1: Offline Training

As discussed above, TRIEDS leverages the unique indoor multipath profile and TR technique to distinguish and detect indoor events. During the offline training phase, we are going to build a database where the multipath profiles of any targets are collected and stored the corresponding TR signatures in the TR space. Unfortunately, due to noise and channel fading, the CSI from a specific state may slightly change over the time. To combat this kind of variations, for each state, we collect several instantaneous CSI samples to build the training set.

Specifically, for each indoor state $S_i \in \mathcal{D}$ with $\mathcal{D}$ being the state set, the corresponding training CSI is estimated and form a $\mathbf{H}_i$ as

$$\mathbf{H}_i = \left[\mathbf{h}_{i,t_0},\ \mathbf{h}_{i,t_1}, \ldots, \mathbf{h}_{i,t_{N-1}}\right] \tag{1}$$

where N is the size of the CSI samples for a training state. $\mathbf{h}_{i,t_j}$ represents the estimated CSI vector of state S_i at time t_j and $\mathbf{H}_i$ is named as the CSI matrix for state S_i. An example of estimated indoor CSI obtained by the prototype in Fig. 1 shown in Fig. 4, where the total length of the CSI is 30. From Fig. 4(a), we can find out that there exist at least 10–15 significant multipath components.

The corresponding TR signature matrix $\mathbf{G}_i$ can be obtained by time-reversing the conjugated version of $\mathbf{H}_i$ as

$$\mathbf{G}_i = \left[\mathbf{g}_{i,t_0},\ \mathbf{g}_{i,t_1}, \ldots, \mathbf{g}_{i,t_{N-1}}\right] \tag{2}$$

where the TR signature $g_{i,t_j}[k] = h^*_{i,t_j}[L-k]$. Here, the superscript $*$ on a vector variable represents the conjugate operator. L denotes the length of a CSI vectors and k denotes the index of taps. Then the training database $\mathcal{G}$ is the collection of $\mathbf{G}_i$'s.

B. Phase 2: Online Testing

After constructing the training database $\mathcal{G}$, TRIEDS is ready for real-time indoor events detection. The indoor events detection is indeed a classification problem. Our objective is to detect the state of indoor targets through evaluating the similarity between the testing TR signatures and the TR signatures in the training database $\mathcal{G}$. The raw CSI information is complex-valued and of high dimensions, which complicates the detection problem and increases the computational complexity if we directly treat the CSI as the feature. To tackle this problem, by leveraging the TR technique, we are able to naturally compress the dimensions of the CSI vectors through mapping them into the strength of the spatial–temporal resonances. The definition of the strength of the spatial–temporal resonance is given as follows.

Definition: The strength of the spatial–temporal resonance $\mathcal{TR}(\mathbf{h}_1, \mathbf{h}_2)$ between two CSI samples $\mathbf{h}_1$ and $\mathbf{h}_2$ is defined as

$$\mathcal{TR}(\mathbf{h}_1, \mathbf{h}_2) = \left(\frac{\max_i |(\mathbf{h}_1 * \mathbf{g}_2)[i]|}{\sqrt{\sum_{l=0}^{L-1} |h_1[l]|^2}\sqrt{\sum_{l=0}^{L-1} |h_2[l]|^2}}\right)^2 \tag{3}$$

where "$*$" denotes the convolution and $\mathbf{g}_2$ is the TR signature of $\mathbf{h}_2$ as

$$g_2[k] = h_2^*[L-k-1],\ \ k = 0, 1, \ldots, L-1. \tag{4}$$

When comparing two estimated multipath profiles, they are first mapped into the TR space where each of them is represented as one TR signature. Then the TR spatial–temporal resonating strength is a metric that quantifies the similarity between these two multipath profiles in the mapped TR space. The higher the TRRS is, the more similar two multipath profiles are in the TR space. The resonating strength defined in (3) is similar to the definition of cross-correlation coefficient between $\mathbf{h}_1$ and $\mathbf{h}_2$ as the inner product of $\mathbf{h}_1$ and $\mathbf{h}_2^*$, which is equivalent to $(\mathbf{h}_1 * \mathbf{g}_2)[L-1]$. However, the numerator in (3) is the maximal absolute value in the convolved sequence. This step is important, in terms of combating any possible synchronization error between two CSI estimations, e.g., the first several taps of CSI may be missed or added in different measurements. Hence, due to its robustness to the synchronization errors in the CSI estimation, the TRRS is capable of capturing all the similarities between multipath CSI samples and increasing the accuracy.

During the online monitoring phase, the RX keeps matching the current estimated CSI to the TR signatures in $\mathcal{G}$ to find the one that yields the strongest TR spatial–temporal resonance. The TRRS between the unknown testing CSI $\tilde{\mathbf{H}}$ and state S_i is defined as

$$\mathcal{TR}_{S_i}\left(\tilde{\mathbf{H}}\right) = \max_{\tilde{\mathbf{h}} \in \tilde{\mathbf{H}}} \max_{\mathbf{h}_i \in \mathbf{H}_i} \mathcal{TR}\left(\tilde{\mathbf{h}}, \mathbf{h}_i\right) \tag{5}$$

where $\tilde{\mathbf{H}}$ is a group of CSI samples assumed to be drawn from the same state as

$$\tilde{\mathbf{H}} = \left[\tilde{\mathbf{h}}_{t_0},\ \tilde{\mathbf{h}}_{t_1}, \ldots, \tilde{\mathbf{h}}_{i,t_{M-1}}\right] \tag{6}$$

and M is the number of CSI samples in one testing group, similar to the N in the training phase defined in (1).

Once we obtain the TRRS for each event, the most possible state for the testing CSI matrix $\tilde{\mathbf{H}}$ can be found by searching for the maximum among $\mathcal{TR}_{S_i}(\tilde{\mathbf{H}}),\ \forall\ i$, as

$$S^* = \arg\max_{S_i \in \mathcal{D}} \mathcal{TR}_{S_i}\left(\tilde{\mathbf{H}}\right). \tag{7}$$

The superscript $*$ on S denotes the optimal.

Besides finding the most possible state S^* by comparing the TR spatial–temporal resonances, TRIEDS adopts a threshold-trigger mechanism, in order to avoid false alarms introduced by events outside of the state class $\mathcal{D}$. TRIEDS reports a change of states to S^* only if the TRRS $\mathcal{TR}_{S^*}(\tilde{\mathbf{H}})$ reaches a predefined threshold γ

$$\hat{S} = \begin{cases} S^*, & \text{if } \mathcal{TR}_{S^*}\left(\tilde{\mathbf{H}}\right) \geq \gamma \\ 0, & \text{otherwise} \end{cases} \tag{8}$$

where $\hat{S} = 0$ means the state of current environment is not changed, i.e., TRIEDS is not triggered for any trained states in $\mathcal{D}$. According to the aforementioned detection rule, a false alarm for state S_i happens whenever a CSI is detected as $\hat{S} = S_i$ but it is not from state S_i.

Although the algorithm for TRIEDS is simple, the accuracy of indoor events detection is high and its performance is validated through multiple experiments in the next section.

IV. Experimental Evaluation

To empirically evaluate the performance of TRIEDS, we conduct several experiments for door states detection in a commercial office environment with different TX–RX locations.

To begin with, a simple LOS experiment for validating the feasibility of TRIEDS is conducted in a controlled environment, with seven TX locations, one RX location and two events. Then, the validation is further extended to both LOS and NLOS cases in a controlled office environment with three RX locations, 15 locations for TX and eight targeted doors made of wood. Meanwhile, experiments are conducted in an uncontrolled indoor environment during normal working hours with people around. Furthermore, the performance of the proposed TRIEDS is also compared with that of the RSS-based indoor monitoring approach, which can be easily extracted from the channel information and classified the using k-nearest neighbor method. To further evaluate the accuracy of the proposed TRIEDS in real environments, the performance of TRIEDS with intentional HMs is studied. Last but not least, results of TRIEDS being as a guard system to secure a closed room are discussed.

A. Experimental Setting

The prototype of the proposed TRIEDS requires one pair of single-antenna TX and RX that work on the ISM band with the carrier frequency being 5.4 GHz and a 125 MHz bandwidth. Moreover, during the experiment, the system runs with a channel probing interval around 20 ms. A snapshot of the hardware device for TRIEDS is shown in Fig. 1 with the antenna installed on the top of the radio box.

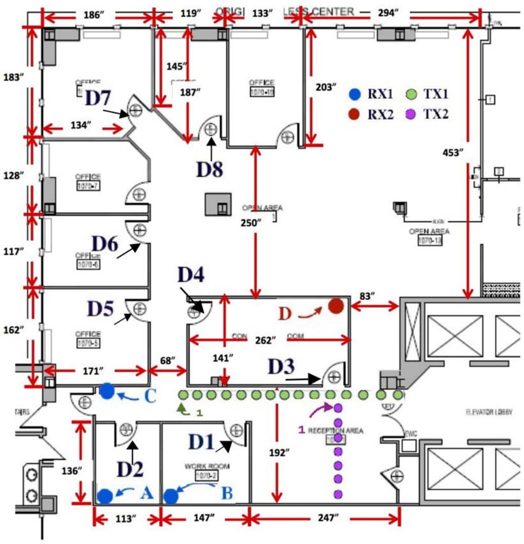


Fig. 5. Floorplan of the test environment.

(a) (b)

Fig. 6. Experiment setting. (a) TX. (b) RX.

The experiments are carried out in the offices at the tenth floor in a commercial building of 16 floors in total. The experimental offices are surrounded by multiple offices and elevators. The detailed setup is shown the floorplan in Fig. 5 where different dotted marks represent different locations for the TX and the RX. During the experiments, we are detecting the open/close states of multiple wooden doors labeled as D1 to D8. Each location for the TX, marked as small round dots and labeled by "TX1" and "TX2," are separated by 0.5 m, whereas the candidate locations for the RX are marked as large round dots by A to "D." The TX–RX locations include both LOS and NLOS transmissions.

In TRIEDS experiments, the RX and the TX are placed on the top of stands at the intended locations, with the height from the ground being 4.3 and 3.6 ft, respectively, as shown in Fig. 6(a) and (b).

In all the experiments, we choose the number of the training CSI and the testing CSI to be $N = 10$ and $M = 10$ as defined in (1) and (6).

B. Feasibility Validation

To begin with, the feasibility for the proposed TRIEDS to detect indoor events is verified in an LOS case where the RX

TABLE I
PERFORMANCE OF THE PROPOSED TRIEDS IN EASY CASE

Location Index	1	2	3	4	5	6	7
False Alarm Rate	0	0	0	0	0	0	0
Detection Rate	1	1	1	1	1	1	1

is placed at the location D in Fig. 5, the TX is moving along the seven purple dots in a vertical line in Fig. 5 with the dot closest to the targeted door labeled as index "1." Our task is to detect whether the wooden door D3 is close or open.

The multipath CSI samples for D3 open and close are obtained through TR channel probing phase and the corresponding TR signatures are stored in the database. In the testing phase, we keep listening to the multipath channel and matching the collected testing CSI to the database for. With any threshold γ smaller than 0.97, we can achieve the perfect detection for all the seven TX locations as in Table I.

In this case, the proposed TRIEDS indeed performs a detection for the events on the LOS path between the TX and the RX. Through this simple experiment, we have demonstrated the feasibility of TRIEDS to use the TR spatial–temporal resonance to capture the changes in the indoor multipath environment. Next, the performance of TRIEDS is further evaluated under more complicated changes of the multipath environment and with both LOS and NLOS TX–RX transmissions.

C. Single Door Monitoring

In this part, the experiments are conducted to understand how locations of the RX, the TX and the targeted objects affect the performance of TRIEDS. The RX is placed at location A, B, and C, whereas the TX is moving along the 15 locations marked by green dots and separated by 0.5 m in a horizontal line as shown in Fig. 5. The objective of TRIEDS is to monitor the states of wooden door D1. During the experiment, for each location and each indoor event, we measure 3000 samples of the CSI which lasts about 5 min by using our built prototype, leading to a total experimental time to be 10 min for each TX–RX location.

Here, the location A (LOC A) represent a throuth-the-wall detection scenario in the absence of an LOS path between the TX and the RX, and between the RX and where the indoor event happens. Under the case when the RX is at the location B (LOC B), there is always an LOS path between the RX and where the indoor event happens, since they are in the same room. However, the LOS path between the TX and the RX disappears regarding most of the possible TX locations, and it exists only if the TX, the RX and the door D1 form a line. However, the TX and the RX always perform LOS transmission when the RX is at the location C (LOC C). Meanwhile, the door D1 to be detected falls outside of the LOS link between the TX and the RX.

1) LOC A (NLOS Case): As we discussed above, when the RX is on LOC A, there is no LOS path between the RX and the TX, and the RX and door D1 are isolated by walls. One example of the multipath CSI for the open and the close state of door D1 is shown in Fig. 7. In Fig. 7 where only

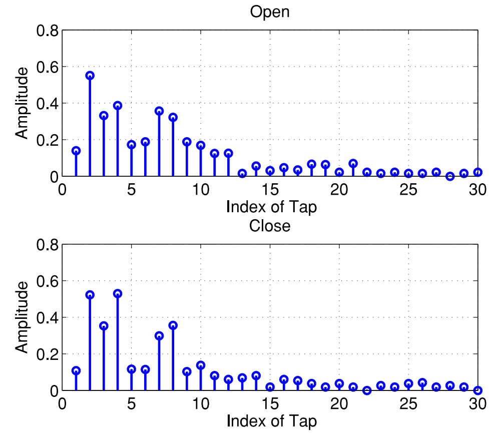


Fig. 7. Multipath profiles (amplitude part) of door D1 under LOC A.

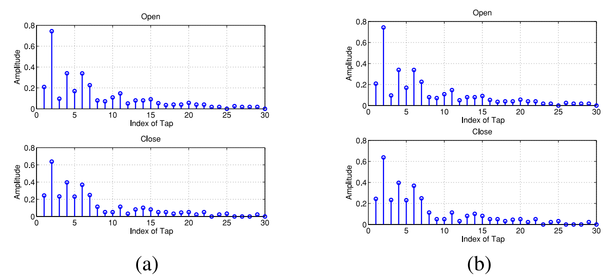


Fig. 8. Multipath profiles of door D1 under LOC B. (a) Multipath profiles (amplitude part) when TX on location 1 (NLOS). (b) Multipath profiles (amplitude part) when TX on location 5 (LOS).

the amplitudes of the CSI are plotted, it is clear to observe a change in how the energy is distributed on each tap. In the proposed TRIEDS, not only the amplitude information but also the phase for each tap is taken into consideration by means of the TR spatial–temporal resonance.

From the experiment, with a threshold γ no larger than 0.9, we can achieve a perfect detection rate and zero false alarm rate for all 15 TX locations. Hence, we can conclude that TRIEDS is capable of detecting an event in an NLOS environment with through-the-wall detection and the distance between the RX and the TX has little effect on the performance.

2) LOC B (LOS and NLOS Case): When the RX is on LOC B, as the TX moving from the location "1" to the location 4 (the fourth dot right to the one marked as 1), the transmission scenario between the TX and the RX is NLOS due to the absence of a direct LOS link. Then, the transmission scenario become LOS, when the TX is on the location "5" to the location "6." When the TX moves farther away (i.e., from the dot "7"), there is no LOS path again between the TX and the RX and the transmission scenario becomes NLOS. In Fig. 8(a) and (b), examples of the CSI for each event are plotted to demonstrate the changes in the amplitudes of the multipath profile corresponding to the indoor event.

Considering the accuracy for TRIEDS, with a threshold $\gamma \leq 0.9$, the detection rate for all 15 TX locations is higher than 99.9%. Except when the TX is at the location 6, the detection probability drops to 95.9%. Nevertheless, the corresponding false alarm rates are all below 0.1%. Since the

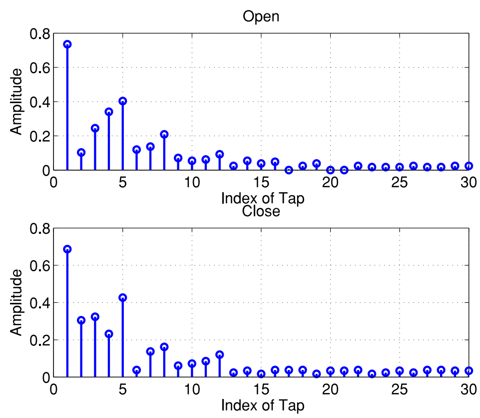


Fig. 9. Multipath profiles (amplitude part) of door D1 under LOC C.

experiment is carried out in a commercial office building, there exist outside activities that we cannot control but indeed change the multipath CSI to fall out the collected indoor events. So the reason for the detection probability at the sixth location being 95.9% might be the existence of uncontrollable outside activities. For example, the elevator running which may greatly change the outside multipath propagation because it is close to the environmental office and is made of metal. Moreover, generally, TRIEDS is robust to the various distances between the TX and the RX and where the indoor event happens.

3) LOC C (LOS Case): When the RX is on LOC C, no matter which green dot the TX is on, they are transmitting under LOS scenario, which leads to a dominant multipath component exists in the multipath CSI.

The LOS transmission brings difficulties to indoor events detection when event locates outside of the LOS path between the TX and the RX. The reason for that can be decomposed into two parts. In the first place, in this experiment, the object door D1 is located parallel with the transmission link between the TX and the RX, and has little influence to the dominant LOS component in the multipath profile. Second, since more energy is focused on the LOS path dominant in the CSI, the other multipath components that contain the event information are more noise-like and less informative. Hence, as most of the information for the event is buried in the CSI components with only a few energy, it is hard to detect an event happening outside the direct link between the TX and the RX in an LOS-dominant wireless system. This can be shown by an example of the multipath CSI with respect to the open and close states of door D1 in Fig. 9, where the dominant path remains the same and contains most of the energy in the CSI.

In the experiment, TRIEDS yields a 100% detection rate and a 0 false alarm rate for all the 15 TX locations with the threshold $\gamma \leq 0.93$. The experimental result supports our claim that the proposed TRIEDS can capture even minor changes in the multipath profile by using TR technique.

D. TRIEDS in Controlled Environments

In the previous sections, we have validated the capability of the proposed system of detecting two indoor events with both LOS and NLOS transmission in controlled indoor environments. In this part, we are going to study the performance of TRIEDS in detecting multiple indoor events. Moreover, the performance comparison between the RSSI-based indoor detecting approach and the proposed TRIEDS is further investigated.

TABLE II
STATE LIST FOR TRIEDS TO DETECT

State index	Description
S_1	All the doors are open.
S_{i+1}	Door Di close and the others open, $\forall i = 1, 2, \cdots, 8$.

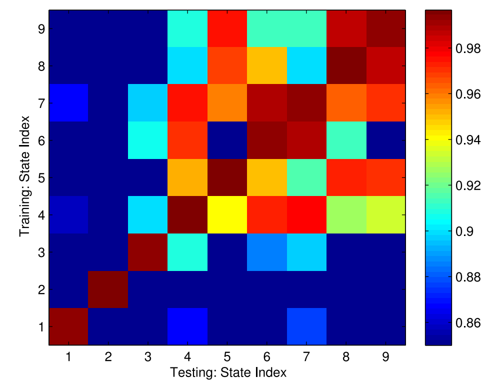


Fig. 10. Resonance strength map with RX on LOC B and TX on the first green dot (axis 1).

In the experiment, the RX is placed on either LOC B or LOC C, whereas the TX moves and stops on every two green dots that are separated by 1 m, named from "axis 1" to "axis 4," respectively. In total, we have two RX locations and four TX locations, i.e., eight TX–RX location. The objective of TRIEDS is to detect which wooden doors among D1–D8 is closed versus all other doors are open, as labeled in Fig. 5. During the experiment, for each TX–RX location and each event, we measure 3000 CSI samples which takes approximately 5 min, leading to a total monitoring time of 45 min. In Table II is the state table describing all the indoor events in the experiment.

As we claimed and verified in the single-event detection experiment that the proposed TRIEDS can achieve highly accurate detection performance by utilizing the spatial–temporal resonance to capture changes in the multipath profiles. In this section, we evaluate the capability of TRIEDS of detecting multiple events in a controlled indoor environment. The performance analysis for normal office environment during working hours will be discussed in Section IV-E.

1) Evaluations on LOC B: To begin with, the performance of TRIEDS when the RX is on LOC B is studied. In Fig. 10, we show how the TRRS varies between different events.

Due to the fact that door D5 and D6 are close to each other whereas they are far away to the RX and the TX, the introduced changes in the multipath profiles of both of them are similar. Consequently, the resonance strength between states S_6 and S_7 is relatively higher than other off-diagonal elements, but it is still smaller than the diagonal ones in Fig. 10 that

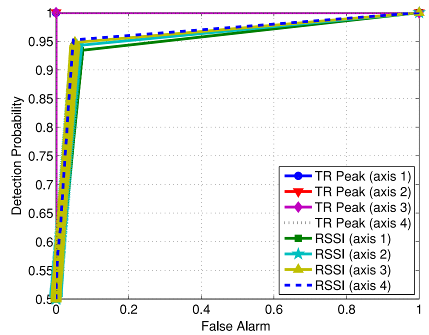


Fig. 11. ROC curve for distinguishing between S_1 and S_2 under LOC B.

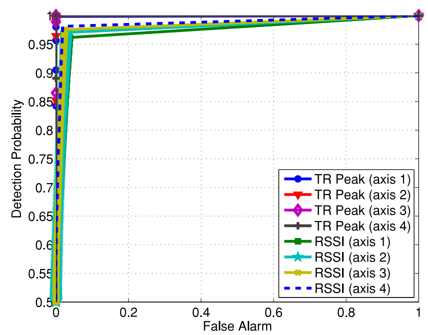


Fig. 12. ROC curve for distinguishing between S_1 and S_9 under LOC B.

TABLE III
FALSE ALARM AND DETECTION PROBABILITY FOR MULTIEVENT DETECTION ON LOC B IN CONTROLLED ENVIRONMENT

LOC B	axis 1	axis 2	axis 3	axis 4
Detection Rate TRIEDS (%)	99.12	99.5	99.67	99.81
False Alarm TRIEDS (%)	0.88	0.5	0.33	0.19
Detection Rate RSSI (%)	89.41	91.16	92.07	93.07
False Alarm RSSI (%)	10.59	8.84	7.93	6.93

represent the in-class resonance strength. Similar phenomenon happens between states S_8 and S_9.

In Figs. 11 and 12, examples of the RX operating characteristic (ROC) curves for detecting states of indoor doors are plotted for both the proposed TRIEDS system and the conventional RSSI approach. Here, the legend "axis i," $i = 1, 2, 3, 4$, denotes the location of TX to be on the $(2*i-1)$th green dot in Fig. 5.

As shown by Figs. 11 and 12, the proposed TRIEDS outperforms the RSSI-based approach in distinguishing between one door is close (i.e., $S_i,\ i \geq 1$) versus all doors are open (i.e., S_0), by achieving perfect detection and zero false alarm rate. Note that S_9 is the state of door D8 which is blocked from the TX–RX link by a close office, as an example, Fig. 11 demonstrates the superiority of TRIEDS in performing a through-the-wall detection. Meanwhile, the performance of the RSSI-based approach degrades as the distance between where the indoor event happens and the TX–RX gets smaller. By leveraging the TR technique, TRIEDS is capable of capturing the changes in a multipath environment in a form of multidimensional and complex-valued vector with high degree of freedoms, and of distinguishing between different changes in the TR spatial–temporal resonance domain. However, the RSSI-based approach tries to monitor the changes in the environment through a real-valued scalar, which due to its dimension loses most of the distinctive information.

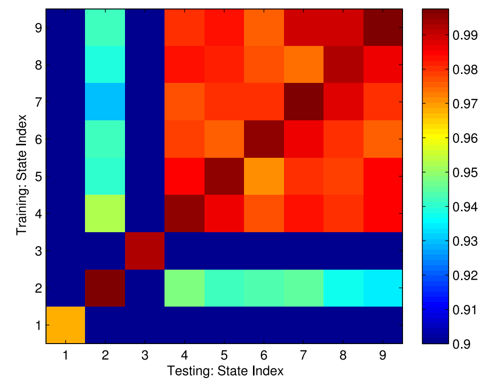


Fig. 13. Resonance strength map with RX on LOC C and TX on the first green dot (axis 1).

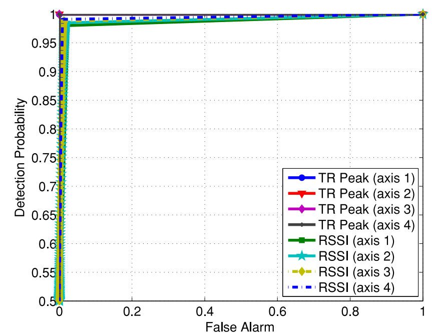


Fig. 14. ROC curve for distinguishing between S_1 and S_2 under LOC C.

Furthermore, the accuracy of detection of TRIEDS improves as the distance between the TX and the RX increases. So does the RSSI-based method. The reason is that when the TX and the RX get far away, more energy will be distributed to the multipath components with longer distance and thus the sensing system will have a larger converage. The overall performance obtained by averaged on all possible events shows that TRIEDS outperforms the RSSI approach in Table III.

2) Evaluations on LOC C: Experiments are further conducted to evaluate the performance of indoor multiple events detection in an LOS transmission scenario by putting the RX on LOC C. In Fig. 13, we show the strengths of the TR spatial–temporal resonances between different indoor events. When the RX and the TX transmit in an LOS setting, the CSI is LOS-dominant such that the energy of the multipath profile is concentrated only on a few taps. It makes the coverage of TRIEDS shrink and degrades the performance of TRIEDS, especially when the indoor events happen far from the TX–RX link as shown in Fig. 13.

Examples of ROC curves to illustrate the detection performance of both TRIEDS and the RSSI-based approach are plotted in Figs. 14 and 15. The performance of the proposed TRIEDS working in an LOS environment is similar

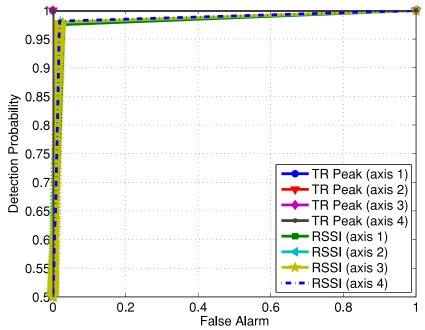


Fig. 15. ROC curve for distinguishing between S_1 and S_9 under LOC C.

TABLE IV
FALSE ALARM AND DETECTION PROBABILITY FOR MULTIEVENT DETECTION ON LOC C IN CONTROLLED ENVIRONMENT

LOC C	axis 1	axis 2	axis 3	axis 4
Detection Rate TRIEDS (%)	99.09	99.28	99.31	99.35
False Alarm TRIEDS (%)	0.91	0.72	0.69	0.65
Detection Rate RSSI (%)	97.24	97.66	97.8	97.88
False Alarm RSSI (%)	2.76	2.34	2.2	2.12

to that in an NLOS environment. Generally, TRIEDS achieves a better accuracy for events detection with a lower false alarm rate, compared with the RSSI-based approach. In both scenarios, TRIEDS achieves almost perfect detection performance in differentiating between $S_i, i \geq 1$ and S_0. Moreover, the RSSI method has a better accuracy in the LOS case than that in the NLOS case.

The corresponding overall performance comparison for TRIEDS and the RSSI-based method is shown in Table IV. It is obvious that the farther the RX and the TX are separated, the better accuracy TRIEDS achieves. Moreover, compared with Table III, the accuracy of RSSI-based method improves a lot in LOS environment, whereas the one of TRIEDS degrades slightly. Moreover, comparing the results in Tables III and IV, the detection performance for TRIEDS degrades a little when the RX and the TX change the transmission scheme from NLOS to LOS. As of the dominant LOS path in LOS transmission, the ability to perceive multipath components which is far away from the direct link degrades, leading to a worse detection accuracy.

E. TRIEDS in Normal Office Environments

In this section, we repeat the experiments in Section IV-D during working hours in weekdays where approximately ten individuals are working in the experiment area, and all offices surrounding and locating beneath or above the experimental area are occupied with uncontrollable individuals.

The proposed TRIEDS achieves similar accuracy compared with that of the controlled experiment in Section IV-D. The overall false alarm and the detection rate for TRIEDS and the RSSI-based approach are shown in Tables V and VI.

The results in Tables V and VI are consistent with the results in Tables III and IV. The performance for TRIEDS is superior to that of the RSSI-based approach, by realizing a better detection rate and a lower false alarm rate. Even in the dynamic environment, the proposed TRIEDS can maintain a detection rate higher than 96.92% and a false alarm smaller than 3.08% under the NLOS case, whereas a detection rate higher than 97.89% and a false alarm smaller than 2.11% under the LOS case. Moreover, as the distance between the RX and the TX increases, the accuracy of both methods improves. In the comparison of Tables III–VI, we claim that the proposed TRIEDS has a better tolerance to the environment dynamics.

TABLE V
FALSE ALARM AND DETECTION PROBABILITY FOR MULTIEVENT DETECTION OF TRIEDS IN NORMAL ENVIRONMENT (LOC B)

LOC B	axis 1	axis 2	axis 3	axis 4
Detection Rate TRIEDS (%)	96.92	98.95	99.23	99.4
False Alarm TRIEDS (%)	3.08	1.05	0.77	0.6
Detection Rate RSSI (%)	92.5	94.16	94.77	95.36
False Alarm RSSI (%)	7.5	5.84	5.23	4.64

TABLE VI
FALSE ALARM AND DETECTION PROBABILITY FOR MULTIEVENT DETECTION OF TRIEDS IN NORMAL ENVIRONMENT (LOC C)

LOC C	axis 1	axis 2	axis 3	axis 4
Detection Rate TRIEDS (%)	97.89	98.94	99.18	99.36
False Alarm TRIEDS (%)	2.11	1.06	0.82	0.64
Detection Rate RSSI (%)	96.73	97.19	97.35	97.43
False Alarm RSSI (%)	3.27	2.81	2.65	2.57

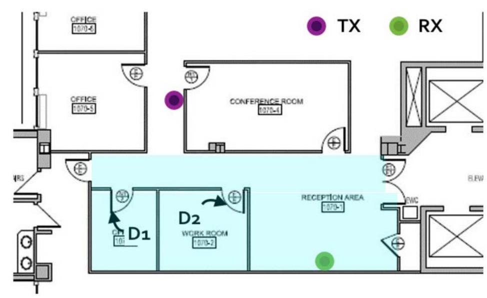


Fig. 16. Experiment setting for study on HMs.

F. TRIEDS With Intentional HMs

To investigate on the effects that the HMs have on the performance of TRIEDS, we conduct experiments with none, one and two individuals keep moving back and forth in the shaded area as Fig. 16 shows. Meanwhile, the TX is put on the purple dot and the RX is on the green dot, detecting the states of two adjacent doors labeled as "D1" and "D2." The list of door states is in Table VII. For each set of experiments, TRIEDS detects the states of the two doors for 5 min during the normal working hours.

TABLE VII
STATE LIST FOR STUDY ON HMS

State	00	01	10	11
D1	Open	Open	Close	Close
D2	Open	Close	Open	Close

TABLE VIII
ACCURACY COMPARISON OF TRIEDS UNDER HMS

Experiment	No HM	One HM	Two HM
No Smoothing	97.75%	87.25%	79.58 %
With Smoothing	98.07%	94.37%	88.33 %

Interference caused by the HMs changes the multipath propagation environment and brings in the variations in the TR spatial–temporal resonances during the monitoring process of TRIEDS. Fortunately, due to the mobility of human, the introduced interference keeps change and the duration for each interference is short. To combat the resulted bursted variations in the TRRSs, we adopt the majority vote method combined with a sliding window to smooth the detection results over time. Supposing we have the previous $K-1$ outputs S_k^*, $k = t-K+1, \ldots, t-1$ and the current result S_t^*, then the decision for time stamp t is made by majority vote over all $S_k^*, k = t-K+1, \ldots, t$, so on and so forth for all t. K denotes the size of the sliding window for smoothing.

In Table VIII, we compare the average accuracy over all states for TRIEDS with or without the smoothing algorithm in the absence of HMs, and in the presence of the intentional persistent HMs performed by one individual and two individuals. Here, the length of the sliding window is $K = 20$. First of all, the accuracy of TRIEDS reduces as the number of individuals increases, performing persistent movements near the location of the indoor events to be detected, the TX and the RX. Moreover, the adopted smoothing algorithm improves the robustness of TRIEDS to HMs and enhances the accuracy by 7%–9% compared with that of the case without smoothing. Meanwhile, during the experiments, we also find that the most vulnerable state is state “00” where all doors are open, such that with HMs TRIEDS is more likely to yield a false alarm than other states. The reason is that as human moves close to the door location, the human body, viewed as an obstacle at the door location, is similar to a close wooden door, and hence the changes in the multipath CSI are also similar, especially for D1.

G. TRIEDS for Through-the-Wall Guard

Unlike the previous experiments where we are trying to detect the door states, in this part, TRIBOD is functioning as a through-the-wall guard system. The objective for TRIEDS is to secure a target room through walls and to alarm not only when the door state changes but also when unexpected HMs happen inside the secured room. The system setup is shown in Fig. 17, where the secured room is shaded.

In this experiment, the TX and the RX of TRIEDS, marked as purple and green dots, are placed in two rooms, respectively, as shown in Fig. 17. TRIEDS is aimed to monitor and

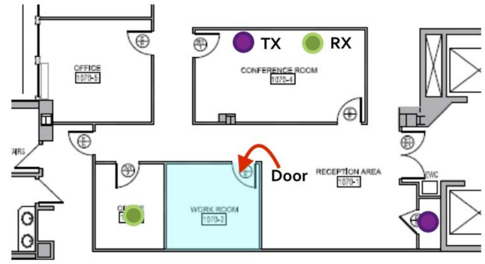


Fig. 17. Experiment setting for guarding.

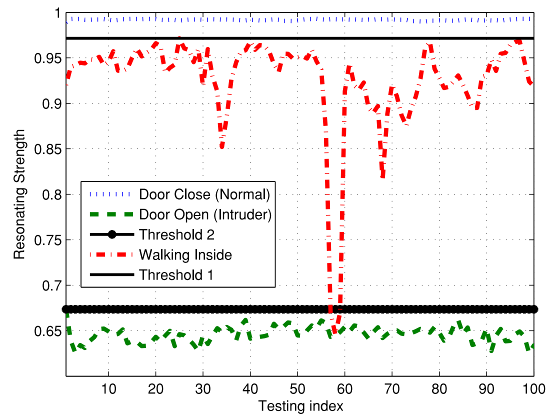


Fig. 18. Resonating strength of guard system.

secure the room in the middle, which is shaded in light blue color, and to report as soon as the door of the secured room is open or someone is walking inside the secured room. TRIEDS only collects the training data for normal state, i.e., door is closed and no one is walking inside the room. The training database consists of ten samples of the CSI. Once TRIEDS starts monitoring, it will keep sensing the indoor multipath channel profile, and compare it with the training database by computing the time reversal resonance strength according to (3) and (5).

An example is shown in Fig. 18, where we can see a clear cut between the normal state and the intruder state, and between the normal state and the state where someone is walking inside the room. The *threshold 1* is the threshold for detecting when the indoor states deviates from the normal state, leading to a 100% detection rate and 0 false alarm. Whereas the *threshold 2* is for differentiating between the intruder state (i.e., door is open) and the state when someone is walking inside the secured room with the door is close, based on which TRIEDS only has 3% error by classifying the human activity state as the intruder state. Even with a single-class training dataset, TRIEDS is capable of distinguishing between different events and functioning as an alarm system to secure the rooms through the walls.

V. DISCUSSION

A. Experimental Parameters

1) *Sampling Frequency:* In this paper, the sampling frequency of TRIEDS is 50 Hz, i.e., TRIEDS senses the multipath environment every 20 ms. Since usually the

changes of door states happen in 1 to 2 s, current sampling frequency is enough for capturing binary changes for doors. In order to detect and monitor the entire transition of the changes or other changes happen in a sudden, a higher sampling frequency is indispensable.

2) *Size of Training and Testing Group:* In the current experiments, we choose both the training group size M in (1) and the testing group size N in (6) as 10, to address the variations of noise in the CSI estimation. We have studied the performance of TRIEDS with different sizes of training and testing group. It is found out that with a size greater than 10, the performance does not improve much but a larger delay for acquiring more CSI samples is introduced. Hence, in this paper, without sacrificing the time sensitivity of TRIEDS, the size of ten (i.e., a sensing duration of 0.2 s) is adopted.

B. Impact of HMs

TRIEDS utilizes the TR technique to map multipath profiles of indoor events into separate points in the TR space, due to the fact that different indoor events and HMs alter the wireless multipath profiles differently.

In Section IV-G, the experimental results of applying TRIEDS in a through-the-wall guard task are discussed. As shown in Fig. 18, in most cases, given the door close event with no human motions, the TRRS of the same event with human motions drops. However, the degradation in the TRRS introduced by human motions is small, whereas the gap between the TRRS of the door close event and that of the door open event is significantly large. The reason is that due to the small size of human body compared to indoor objects like doors, human body only alters a small portion of multipath components when moving not close to the TX or the RX, resulting in sparse changes in the amplitude or the phase of a couple of taps in the CSI. Consequently, the point of door close event with human motions locates at the “proximity” of the point of the static door close event, i.e., the two points are quite similar measured by the TRRS. They can be viewed as a single cluster given a proper threshold on the TRRS. However, when the human motions are close to the TX or the RX, there is a chance that the altered multipath profile differs a lot from the one of the static indoor event, leading to a great attenuation in the TRRS, and thus a different cluster in the TR space as well as a miss detection in TRIEDS. Moreover, as discussed in Section IV-F, the detection accuracy drops compared to the case without intentional motions with intentional HMs. It is because that due to the existence of moving human bodies, the CSI or the multipath profiles in the environment deviate accordingly and keep changing. However, with the help of smoothing over the time domain, the dynamic changes in multipath profiles introduced by human motions can be trimmed out.

C. Future Work

This paper validates the feasibility and capability of TRIEDS in detecting indoor events and evaluates its performance through experiments in real environments. We also recognize several limitations of the existing system and potential applications that motivate future work.

1) In this paper, the capability of the proposed TRIEDS is only validated and evaluated through the experiments to detect the states of multiple doors with the existence of HMs in an office environment. In fact, TRIEDS is suitable for many other indoor events, such as monitoring the states of windows, and differentiating between different HMs. In the next step, we are going to conduct more experiments on detecting other events.
2) As the first to apply TR technique to indoor event detections, this paper is aimed to illustrate the feasibility and capability of TRIEDS in detecting events in indoor environments with the simplest training and testing mechanism to produce acceptable results and performance. Moreover, a prototype of the TR indoor event detection system is built and put into experiments in real indoor environments to test the performance of TRIEDS. Advanced training and testing algorithms, e.g., the machine learning technique, will improve the performance of the TR indoor event detection system. However, this is beyond the scope of this paper and we plan to investigate it in the next step.
3) Equipped with only one pair of the TX and the RX, the current system can yield a good detection accuracy for indoor events. However, by deploying more transceiver pairs, the performance of TRIEDS can be improved as the captured multipath profiles contain information with more degrees of freedoms coming from the spatial diversity. We plan to explore the use of multiple TXs or RXs to acquire the gain in spatial diversity for further performance improvement of TRIEDS.

In spite of these limitations, we believe that the proposed TRIEDS introduce a novel idea to apply the TR technique to capture the variations in the multipath propagation environments for future surveillance systems.

VI. Conclusion

In this paper, we proposed a novel wireless indoor events detection system, TRIEDS, by leveraging the TR technique to capture changes in the indoor multipath environment. TRIEDS enables low-complexity devices with the single antenna, operating in the ISM band to detect indoor events even through the walls. TRIEDS utilizes the TR spatial–temporal resonances to capture the changes in the EM propagation environment and naturally compresses the high-dimensional features by mapping multipath profiles into the TR space, enabling the implementation of simple and fast detection algorithms. Moreover, we built a real prototype to validate the feasibility and to evaluate the performance of the proposed system. According to the experimental results for detecting the states of wooden doors in both controlled and dynamic environments, TRIEDS can achieve a detection rate over 96.92% while maintaining a false alarm rate smaller than 3.08% under both LOS and NLOS transmissions.

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