TIME REVERSAL BASED WIRELESS EVENTS DETECTION

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ABSTRACT

In this work, we propose a novel wireless time-reversal indoor events detection system (TRIEDS). By leveraging the time-reversal (TR) 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 multiple events detection. 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 a 125 MHZ bandwidth. Experiments are conducted to monitor the states of the indoor wooden doors. Experimental results show that with a single receiver (AP) 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, time reversal (TR), wireless events detection, spatial-temporal resonance, through the wall.

1. 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.

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 [1–3]. However, conventional vision-based indoor monitor systems have many limitations, such as the requirement of an illuminated line-of-sight (LOS) path and privacy leakage due to malicious internet attacks.

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 changes in the environments. Due to its susceptibility to the environmental changes, the received signal strength indicator (RSSI) has been applied to indicate and further recognize indoor activities [4,5]. Furthermore, CSI information, including the amplitude and the phase, is now accessible in many commercial devices and has been used for indoor event detection [6–9]. Another category of technologies in device-free indoor monitor systems is adopted from radar imaging technology to track targets by identifying different time-of-flights (ToF) of wireless signals through different paths using ultrawide-band (UWB) [10]. However, the UWB transmission, which is required to have a fine resolution in ToFs, is impractical in commercial indoor monitoring systems, because it requires specific hardwares for implementation. Recently, Katabi *et al.* proposed a new radar-based system to keep track of different ToFs of reflected signals by leveraging a specially designed frequency modulated carrier wave (FMCW) that sweeps over different carrier frequencies [11–13]. But their techniques consume over 1GHz 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 ultra-wideband to capture features that can guarantee the accuracy of detection. In contrast, in this work, 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. As originally investigated in the phase compensation over telephone line [14], TR technique was then extended to the acoustics [15]. TR technique treats each path of the multipath channel in a rich scattering environment as a widely distributed virtual antenna and

Fig. 1: Prototype of TRIEDS.

provides a high-resolution spatial-temporal resonance, commonly known as the focusing effect [16]. 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.

A novel TR-based indoor localization approach, namely TRIPS, was proposed in [17] and has been implemented on a WiFi platform [18]. Through non-line-of-sight (NLOS) experiments, TRIPS achieved a perfect 5cm precision with a single access point (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.

By utilizing TR technique to capture small variations in the multipath CSI, TRIEDS is capable of performing highly accurate indoor events detection. To evaluate the performance of the proposed system, we build a TR wireless system prototype as shown in Figure 1 that operates at 5.4 GHz band with a bandwidth of 125 MHz. We conduct experiments in an indoor 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 work is organized as follows. The essential technique, TR, is introduced in Section 2 and the system model, as well as the methodology that TRIEDS adopts is described in Section 3. The performance of the proposed TRIEDS is evaluated through experiments conducted in real environments and the results are discussed in Section 4.

2. TIME-REVERSAL TECHNIQUE

A typical TR wireless communication system is shown in Figure 2 [19]. During the channel probing phase, the transceiver B sends an impulse to the transceiver A, which gets an esti-

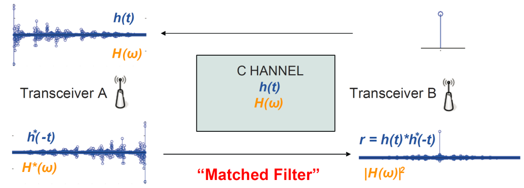


Fig. 2: TR-based wireless communication.

mated 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 [16]. As long as the indoor propagation environment changes, the received multipath profile varies correspondingly. As a consequence, the spatial-temporal resonance at the receiver side changes and can be used to track the events in the indoor environment.

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 indoor environments and detects indoor events by utilizing TR technique. In TRIEDS, the complex-valued multipath CSI are treated as feature vectors that directly represent each indoor events, and the TR technique is applied to reduce the dimension of features for classification.

3. 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 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: the offline training and the online testing.

3.1. Phase 1: Offline Training

During the offline training phase, a database is built where the multipath profiles of any targets are collected and stored as the TR signatures. Unfortunately, due to noise and channel fading, the CSI from a specific state may slightly change over the time. To combat that, for each state, we collect several instantaneous CSI samples for each state. Specifically, for each indoor state $S_i \in \mathcal{D}$ with $\mathcal{D}$ being the state set, the corresponding training CSI samples are estimated and form a $\mathbf{H}_i$ as,

$$\mathbf{H}_i = [\mathbf{h}_{i,t_0},\ \mathbf{h}_{i,t_1},\ \cdots,\ \mathbf{h}_{i,t_{N-1}}], \quad (1)$$

where N is the size of 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. The corresponding TR signature matrix $\mathbf{G}_i$ can be obtained by time-reversing the conjuagted version of $\mathbf{H}_i$ as:

$$\mathbf{G}_i = [\mathbf{g}_{i,t_0},\ \mathbf{g}_{i,t_1},\ \cdots,\ \mathbf{g}_{i,t_{N-1}}], \quad (2)$$

where the TR signature $\mathbf{g}_{i,t_j}[k] = \mathbf{h}^*_{i,t_j}[L-k]$ is the time-reversed and conjugated version of $\mathbf{h}_{i,t_j}$. Here, the superscript $*$ on a vector variable represents the conjugate operator. L denotes the length of CSI and k denotes the index of taps.

Then the training database $\mathcal{G}$ is the collection of $\mathbf{G}_i$'s.

3.2. Phase 2: Online Testing

After constructing the training database $\mathcal{G}$, TRIEDS is ready for real-time indoor state detection, which is indeed a classification problem. Our objective is to detect the state through matching its multipath profiles to TR signatures in the training database $\mathcal{G}$. By leveraging the TR technique, we are able to naturally compress the dimensions of the CSI 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 (TRRS) $\mathcal{TR}(\mathbf{h}_1, \mathbf{h}_2)$ between two CSI samples $\mathbf{h}_1$ and $\mathbf{h}_2$ is defined as

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

where "$*$" denotes the convolution and $\mathbf{g}_2$ is the TR signature of $\mathbf{h}_2$ as, $g_2[k] = h_2^*[L-k-1],\ k = 0, 1, \cdots, L-1$.

The similarity between CSI samples are quantified by the value of TRRS. When comparing the estimated CSI with the TR signature in the database, only when CSI samples are from the identical state there will be a strong spatial-temporal resonance.

During the online monitoring phase, the receiver keeps matching the current estimated CSI to the TR signature in $\mathcal{G}$ to find the one that yields the strongest TR spatial-temporal resonance, computed by the testing CSI matrix $\tilde{\mathbf{H}}$ and the signature matrix $\mathbf{G}_i$ for each trained states S_i. The strength of the TR spatial-temporal resonance between the unknown testing CSI samples $\tilde{\mathbf{H}}$ and state S_i is defined as

$$\mathcal{TR}_{S_i}(\tilde{\mathbf{H}}) = \max_{\tilde{\mathbf{h}} \in \tilde{\mathbf{H}}} \max_{\mathbf{h}_i \in \mathbf{H}_i} \mathcal{TR}(\tilde{\mathbf{h}}, \mathbf{h}_i), \quad (4)$$

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

$$\tilde{\mathbf{H}} = [\tilde{\mathbf{h}}_{t_0},\ \tilde{\mathbf{h}}_{t_1},\ \cdots,\ \tilde{\mathbf{h}}_{i,t_{M-1}}], \quad (5)$$

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

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

$$\hat{S} = \begin{cases} S^*, & \text{if } \mathcal{TR}_{S^*}(\tilde{\mathbf{H}}) \geq \gamma, \\ 0, & otherwise, \end{cases} \quad (6)$$

where $S^* = \arg\max_{S_i \in \mathcal{D}} \mathcal{TR}_{S_i}(\tilde{\mathbf{H}})$. $\hat{S} = 0$ 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 sample 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.

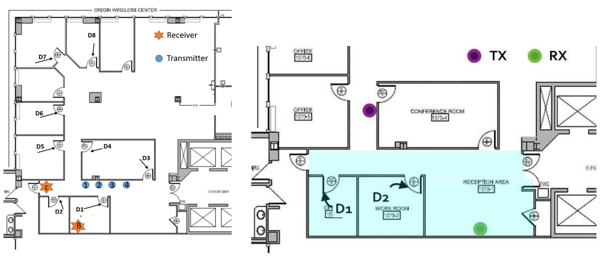
4. EXPERIMENTAL EVALUATION

To empirically evaluate the performance of TRIEDS, we conduct several experiments for door states detection in a commercial office environment during working hours where approximately 10 individuals are working in the experiment area, and all offices surrounding, locating beneath or above the experimental area are occupied with uncontrollable individuals. To begin with, experiments are conducted to monitor states of multiple doors in an uncontrolled indoor environment. To further evaluate the accuracy in real environments, the performance of TRIEDS under intentional human movements is studied. We choose the number of the training CSI samples and the testing CSI samples to be $N = 10$ and $M = 10$ as defined in (1) and (5), considering the fact that 10 CSI samples corresponds to 0.1 second during which the channel should stay stationary.

4.1. TRIEDS in Normal Office Environments

The detailed setup for this experiment is shown in Figure 3a. During the experiments, we are monitoring the open/close states of multiple wooden doors labeled as D1 to D8. Each location for the transmitter, marked as blue round dots, are separated by 1 meter, whereas receiver are located on large stars with label "B" and "C".

The overall false alarm and the detection rate for TRIEDS and the RSSI-based approach are shown in the Table 1. Even



(a) Experimental setting 1. (b) Experimental setting 2.

Fig. 3: Floor plan of the test environment.

	axis 1	axis 2	axis 3	axis 4
Detection Rate TRIEDS (LOC B)	96.92	98.95	99.23	99.4
False Alarm TRIEDS (LOC B)	3.08	1.05	0.77	0.6
Detection Rate RSSI (LOC B)	92.5	94.16	94.77	95.36
False Alarm RSSI (LOC B)	7.5	5.84	5.23	4.64
Detection Rate TRIEDS (LOC C)	97.89	98.94	99.18	99.36
False Alarm TRIEDS (LOC C)	2.11	1.06	0.82	0.64
Detection Rate RSSI (LOC C)	96.73	97.19	97.35	97.43
False Alarm RSSI (LOC C)	3.27	2.81	2.65	2.57

Table 1: False alarm and detection probability for multi-event detection of TRIEDS in normal environment .

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 transmission (LOC B), whereas a detection rate higher than 97.89% and a false alarm smaller than 2.11% under the LOS transmission (LOC C). Moreover, as the distance between the receiver and the transmitter increases, the accuracy of both methods improves.

4.2. TRIEDS with Intentional Human Movements

To investigate on the effects that the human movements have on the performance of TRIEDS, we conduct experiments with none, one and two individuals keep walking back and forth in the shaded area as shown in Figure 3b. Meanwhile, the transmitter is put on the purple dot and the receiver is on the green dot in the shaded area, monitoring the states of two adjacent doors labeled as “D1” and “D2”.

Interference caused by the human movements changes the multipath propagation environment and brings in the variations in the TR spatial-temporal resonances during the monitoring process of TRIEDS. To combat this, 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 $S_k^*,\ k=t-K+1,\ \cdots,t-1$ and the current result S_t^*, then the decision for time stamp t is made by majority vote over all $S_k^*,\ k=t-K+1,\ \cdots,t$.

Experiment	No HM	One HM	Two HM
w/o SMG	97.75%	87.25%	$79.58\ \%$
with SMG	98.07%	94.37%	$88.33\ \%$

Table 2: Accuracy comparison of TRIEDS under human movements with or without smoothing (SMG).

In Table 2, we compare the average accuracy over all states for TRIEDS with or without the smoothing algorithm. Here, the length of the sliding window is $K=20$. First of all, the accuracy of TRIEDS reduces as the number of individuals performing persistent movements near the targeted objects, the transmitter or the receiver increases. The reason is that the channel multipath profiles vary more severely when the number of present individuals increases, considering the distortions and interference brought by human body. Altered multipath profiles lead to a degradation in detection accuracy of TRIEDS due to the mismatch to the training database. Moreover, the adopted smoothing algorithm improves the robustness of TRIEDS to human movements and enhances the accuracy by 7% to 9% compared with that of the case without smoothing. Meanwhile, during the experiments, we also find that the most vulnerable state is when all doors are open where human movements TRIEDS is more likely to yield a false alarm. 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.

5. CONCLUSIONS

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, which supports 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 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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