TIME REVERSAL INDOOR TRACKING WITH CENTIMETER ACCURACY

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ABSTRACT

In a rich-scattering environment, radio frequency (RF) devices communicate through multipath channels and the channel state information (CSI) is uniquely determined by the location of the transmitter or receiver devices along with surrounding environments. Whenever one of the devices moves, the CSI changes accordingly. In other words, there is a one-to-one mapping between the CSI and the location of RF devices. Inspired by the relationship, we propose a real-time indoor tracking system that utilizes time-reversal (TR) technique to capture differences in the CSI and then accurately locate the moving RF device along its trajectory. Moreover, a real-time speed estimation algorithm is designed based on the spatial distribution of the TR resonance. A prototype is built to validate the accuracy and robustness of the proposed system through a train tracking experiment. It illustrates the TR technique as a promising solution to high-precision indoor tracking applications.

Index Terms**—** Smart radio; time-reversal (TR); indoor tracking; speed estimation.

1. INTRODUCTION

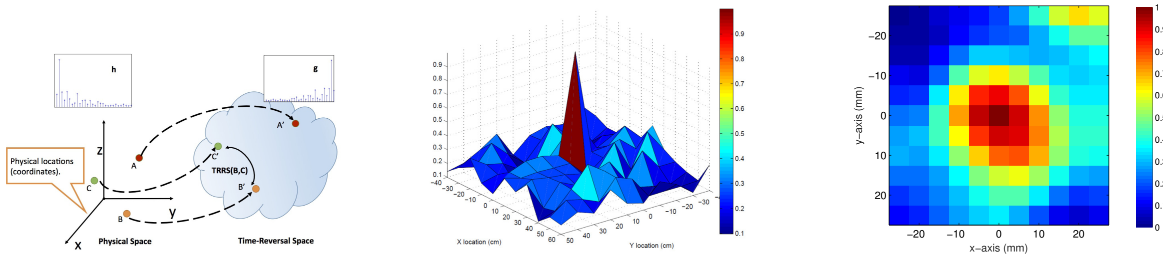
Nowadays, outdoor tracking has been well developed and can achieve a high accuracy with the help of the Global Positioning System (GPS). However, due to the failure of GPS in indoors, the indoor tracking problem which requires high accuracy and low latency is still open for investigation.

The indoor tracking system (ITS) can be viewed as a derivation of the indoor position system (IPS) because in tracking a sequence of locations that form a moving trajectory are to be identified. Most of existing ITSs and IPSs, which depends on triangulation of time-of-flight (ToF) or angle-of-arrival (AoA), requires multiple access points (APs) as anchor points to locate the terminal device (TD) [1–7]. However, there are many scatterers and blockages in a typical indoor environment and introduces multipath channels between AP and TD. Due to the nature of multipath that impairs precise measurement for triangulation, the performance of those systems degrades a lot when there is no line-of-sight (LOS) path for wireless transmission. Other wireless indoor tracking systems rely on isolating target reflected path from other multipaths by using the ultra-wideband transmission or a specially designed frequency sweeping signal [8, 9].

In this paper, we propose a novel indoor tracking system (ITS) that utilizes time-reversal (TR) technique to support high accuracy fixed-path tracking with only one single-antenna AP. TR technique has been proposed as a novel and promising paradigm for Internet of Things (IoT) [10]. In TR, each physical location of the moving TD is linked to a unique multipath profile that can be viewed as a logical location in the TR space. The position of a moving TD is determined by finding a match between the current logical location and a pre-mapped training database, and the similarity between two logical locations can be measured by the TR spatial-temporal resonance strength (TRRS). It has been shown that the TRRS has a peak in the center of the resonance effect, i.e., when the two logical locations belong to the same physical location, and decays rapidly when the two physical locations are different, e.g., even 1-2 centimeter apart. By choosing a proper threshold according to the TRRS decay at a given carrier frequency, the proposed TR based indoor tracking system (TRITS) can achieve centimeter-level accuracy. As there exists a large number of multipaths in indoors, constituting a large number of degree of freedom, and normal human activities can only affect a portion of the multipaths, TRITS is also robust to environment dynamics.

Moreover, by leveraging the spatial distribution of the TRRS, the moving speed of the TD can be estimated without pre-mapping. With the proposed speed estimation algorithm, the tracking system only needs to search within a small portion of the training database that is close to the current estimate position. On the other hand, with the knowledge of the moving speed, a proper sampling rate of the system can be selected to avoid unnecessarily high sampling overhead. Taking advantage of the high-resolution TR spatial-temporal resonance, we show through experiments that each position on the moving trajectory can be located with a centimeter-level accuracy, with low computational complexity and small latency. The proposed TRITS is a promising solution to future high-accuracy indoor tracking applications, especially those with a fixed moving path in manufacture sites, warehouses, and so on.

This paper is organized as follows. In Section 2, the theo-



(a) (b) (c)

Fig. 1: Theoretical foundations of TRITS. (a) TR space: from physical locations to logical locations. (b) Geographic distribution of TRRS: coarse scale (with 5 cm spacing). (c) Geographic distribution of TRRS: fine scale (with 5 mm spacing) [11].

retical foundation behind the proposed system is introduced. The detailed design of the proposed system is discussed in Section 3 and experimental results are in Section 4. Conclusions are drawn in Section 5.

2. PRELIMINARY

In this section, we introduce the theoretical foundation of the proposed indoor tracking system.

2.1. Time-Reversal Technique

TR technique takes advantage of multipath propagation by treating each path in a multipath channel as a distributed virtual antenna, and provides a high-resolution spatial-temporal resonance [11]. When the propagation path changes due to the change of either the TD location or the environment, the resulted spatial-temporal resonance changes correspondingly. The TRRS can quantitatively evaluate the difference between multipath environments represented by the CSI, whose definition is as follows.

Definition: The TRRS between two CSI, a.k.a., channel impulse responses (CIRs), $\mathbf{h}_1$ and $\mathbf{h}_2$ is defined as $\mathcal{TR}(\mathbf{h}_1, \mathbf{h}_2) = \frac{\max_i \left|(\mathbf{h}_1 * \mathbf{g}_2)[i]\right|^2}{\left(\sum_{l=0}^{N_{tap}-1} |h_1[l]|^2\right)\left(\sum_{l=0}^{N_{tap}-1} |h_2[l]|^2\right)}$, and $g_2[l] = h_2^*[N_{tap} - l - 1]$, $l = 0, 1, \cdots, N_{tap} - 1$, where N_{tap} denotes the CIR length, "$*$" is the convolution operator, and $\mathbf{g}_2$ represents the TR signature of CSI $\mathbf{h}_2$.

Recently, thanks to its capability of fully exploiting multipaths, TR has been advocated as a promising paradigm for green IoT in [10] with many cutting-edge IoT applications being proposed and implemented [12–17].

2.2. Indoor Positioning with Centimeter-Level Accuracy

Most of the existing IPS can only achieve a positioning accuracy in the order of meter, and the performance degrades a lot when only a single AP is available and/or under a non-line-of-sight (NLOS) condition [12]. The reason is that they rely on a precise geographical calculation over the measured characteristics of wave propagation, e.g., the time of arrival (TOA) [2], the angle of arrival (AOA) [6], or the received signal strength (RSS) [4] of the probing signal. Due to the rich-scattering nature of an indoor environment, it is difficult to obtain accurate measurements of the aforementioned characteristics of wave propagation, especially under a NLOS case.

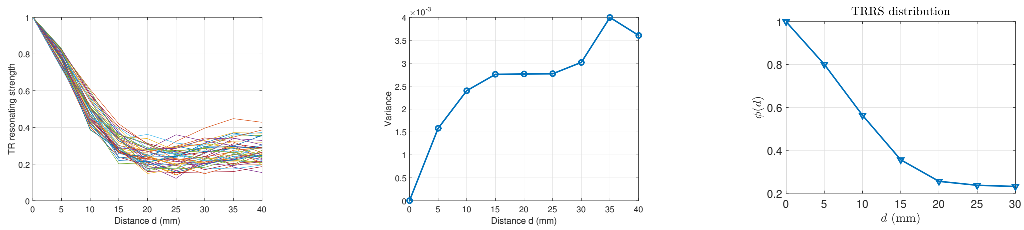
To overcome the bottleneck of existing IPS, a TR based indoor positioning system (TRIPS) was firstly proposed in [12], and a prototype was implemented under a transmission bandwidth of 125 MHz at carrier frequency of 5.4 GHz. Through TR technique, each physical location of the TD (x, y, z) is mapped to a unique logical location in the TR space, represented by the multipath channel $\mathbf{h}_{(x,y,z)}$ or the corresponding TR signature $\mathbf{g}_{(x,y,z)}$. The subscript $(\cdot)_{(x,y,z)}$ denotes the location in a coordinate space where the multipath channel $\mathbf{h}_{(x,y,z)}$ is measured. A demonstration is shown in Fig.1a, where each point in the physical (coordinate) space is one-to-one mapped to a point in the TR space. The geographic distribution of TRRS of CIRs measured at different locations is plotted in Fig.1b and Fig.1c with different scales. Through experiments, it has been verified that the TRRS drops dramatically when two physical locations are more than 1 cm away given the carrier frequency of 5.4 GHz. Hence, the current location of a TD can be determined by matching its associated logical location with the ones stored in the database. As there usually exists a large number of multipaths in a rich-scattering indoor environment, and indoor activities can only affect a limited number of the multipaths, TRIPS also can leverage the large degree of freedom gain brought by the multipaths and is thus robust to normal environment dynamics.

3. CENTIMETER ACCURACY TRACKING

Inspired by the principle of TR and TRIPS, TRITS is proposed and implemented in this work.

3.1. From Physical Trajectory to Logical Trajectory

The essential concept in TRITS is converting the trajectory of a moving TD in the physical space to a logical trajectory in the TR space. Through that, each point on the physical trajectory as represented by a coordinate is mapped into a point



(a) (b) (c)

Fig. 2: TRRS decay curves [16]. (a) TRRS decay of 55 measurements. (b) Sample variance. (c) The mean of TRRS distribution along a line.

in the TR space which is represented by a unique multipath profile. The indoor tracking problem is then transformed to a logical tracking problem where a sequence of logical locations, a.k.a., multipath channel profiles, is to be recognized.

On the other hand, TR technique is an ideal solution to indoor tracking because it quickly and quantitatively measures the difference between logical locations through TRRS, with a low computational complexity and a high spatial resolution of 1 to 2 cm. As the logical tracking problem is solved by adopting TR technique, so does the physical indoor tracking problem given a fixed path.

The proposed TRITS consists of two phases.

1. *The offline mapping phase*: the multipath profile, a.k.a. CIR $\mathbf{h}_{(x,y,z)}$ of each location (x, y, z) on the trajectory $\mathcal{P}$ is estimated and stored in the database as a logical location. Thus, the physical trajectory of a moving TD is converted to the logical trajectory in TR space.
2. *The online tracking phase*: the current location of a moving TD is determined by matching the real-time measured multipath profile $\mathbf{h}_{\text{test}}$ with logical locations in the database collected during offline phase. As long as the TRRS is higher than a predefined threshold Γ, the current location of TD can be determined, i.e.,

$$(x,y,z)^* = \begin{cases} \arg \max\limits_{(x,y,z)\in\mathcal{P}} \mathcal{TR}(\mathbf{h}_{\text{test}}, \mathbf{h}_{(x,y,z)}), \\ \quad \text{if} \max\limits_{(x,y,z)\in\mathcal{P}} \mathcal{TR}(\mathbf{h}_{\text{test}}, \mathbf{h}_{(x,y,z)}) \geq \Gamma \\ \text{unknown}, \quad otherwise \end{cases} \tag{1}$$

In Fig.2, the spatial decay of $\mathcal{TR}(\mathbf{h}_{test}, \mathbf{h}_{(x_0,y_0,z_0)})$ is studied with a resolution of 0.5 cm by collecting CIRs around 55 randomly selected focal spots (x_0, y_0, z_0). The results imply that the TRRS decreases rapidly as the distance between the TD and the focal spot increases, and when the distance exceeds 1 to 2 cm, the TRRS drops below 0.7 with almost probability 1 and a variance smaller than 3×10^{-3}. Hence, the Γ is chosen as 0.7 to guarantee a centimeter-accurate tracking.

3.2. Speed Estimation

To reduce the computation complexity in the online testing phase, we also propose a mapping-free speed estimation algorithm, through which the current speed of the moving TD can be obtained and the searching range of the training database for the incoming CSI measurement can be reduced to the proximity of the current estimated position. Moreover, it is better for TRITS to sample the fixed trajectory at a proper rate such that the distance between two consecutive sampled positions being 1 to 2 cm. With the knowledge of the moving speed, we can determine a proper CSI sampling rate to ensure the sampling resolution while avoiding the unnecessarily high overhead.

As plotted in Fig.2c, the mean TRRS distribution w.r.t. the distance between the sampled positions, i.e., $\phi(d)$, can be obtained by taking a sample average of all the measured TRRS decay curves in Fig.2a. Based on $\phi(d)$, a speed estimation algorithm is described in Algorithm1 [16].

Algorithm 1 TR-based speed estimator

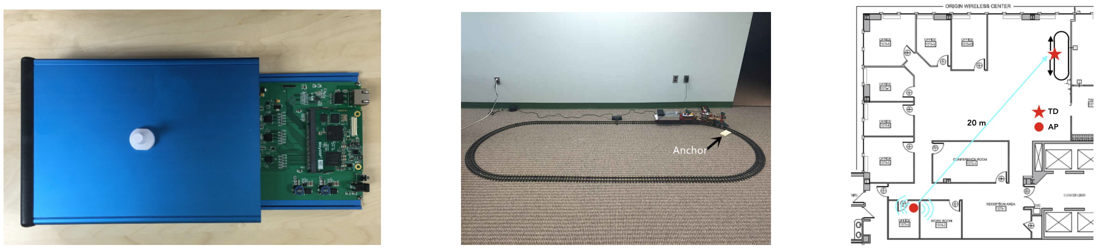
Input: N consecutive CSI measurements: $[\mathbf{h}_{t-N+1}, ..., \mathbf{h}_t]$
Output: Speed estimation at t: $\hat{v}(t)$

Initialization: $\Sigma \leftarrow 0$, T_s (channel probing interval)
for $i \in \{t-N+1, ..., t-1\}$ **do**
  $\Sigma \leftarrow \Sigma + \mathcal{TR}(\mathbf{h}_i, \mathbf{h}_{i+1})$
end for
$\hat{v}(t) = \frac{\phi^{-1}(\Sigma/(N-1))}{T_s}$

3.3. Robustness to Dynamics

Moreover, the proposed TR based indoor tracking technique can survive during normal environmental changes. Thanks to the large number of multipaths in a rich-scattering indoor environment, a large degree of freedom is provided in the CSI. Because normal perturbations of EM waves and surrounding dynamics in the environment only involve a small portion of multipaths, the perturbed CSI can still be used to represent and determine the locations given large degrees of freedom. In other words, multipaths provide not only the accuracy but also robustness in the proposed system.

By exploiting the multipath propagation with TR technique, TRITS is a promising solution to high-accuracy indoor tracking applications, especially those with fixed paths, including manufacture sites, warehouses, and so on.



(a) (b) (c)

Fig. 3: Experimental setting for train tracking. (a) Prototype. (b) Train track. (c) Floorplan.

4. EXPERIMENTAL RESULTS

To demonstrate and validate the concept of TRITS, a prototype of train tracking is built as an example of indoor fixed-path tracking. Equipped with a single omni-direction antenna, the AP and the TD, in Fig.3a, communicates wirelessly in ISM band of 125 MHz bandwidth and 5.4 GHz carrier frequency. The TD is attached to a model train running along a closed track as shown in Fig.3b. The experimental setup is depicted in Fig.3c, and the distance between the AP and the train track is about 20 meters and there is no LOS path. The length of tracks is 8.0 m, and the total time for the train running through one loop is 10.3 seconds. Given the average speed of train being 77.7 cm/s, the channel probing interval between the AP and the TD is set to 100 Hz.

Accuracy Validation: To validate the accuracy of TRITS, we conduct the experiment by arbitrarily selecting an anchor point on the track as the start and the end point, and measuring the running time of the train. Following the steps in Section 3 with a proper threshold Γ, TRITS achieves centimeter-level accuracy as long as it can track the train. When TRITS fails to find a match for the current position and loses track of the running train, a new match can be found and the tracking will resume after the train finishes the current loop and gets back to that position.

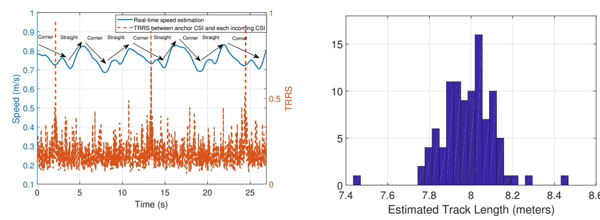
Let T_{TRITS} denote the accumulated running time (with centimeter-accuracy tracking) measured through TRITS, which remains unchanged when TRITS loses track. The accuracy measurement is defined as Accu. $= \frac{T_{\text{TRITS}}}{T_0} \times 100\%$, where T_0 is the ground-truth running time of the train. Through experiments, when the environment is static, an accuracy of 100% is achieved by TRITS.

Robustness Validation: In reality, there always exist environmental dynamics due to human activities. Therefore, an experiment is designed to evaluate the robustness of the proposed system. Propagation perturbations are artificially introduced by one person walking in a certain area, and the experiment in the previous part is repeated to study the performance degradation. The results are listed in Table 1 which shows that TRITS can still work well under normal environment dynamics.

Speed Estimation: In this part, an anchor point on the train track is selected and the TRRSs between all the CIR of the anchor and others CIRs measured during the train running are computed and shown in Fig.4a. The peaks in the red line indicate the train passing the anchor three times with a similar speed depicted by the blue curve. Generally, the train slows down when it makes turns and then speeds up along the straight track. This trend is reflected in the speed estimation. Moreover, the length of the track is estimated by integrating the speed estimates over time for each lap and the results are shown in Fig.4b. The resulted average distance error is 2.1%.

Table 1: Accuracy under different surrounding dynamics.

Area	along the track	inside the track	around the AP	in the open space
Accu.	98.93	98.64	97.95	100



(a) (b)

Fig. 4: Experimental results for speed estimation. (a) Speed estimation. (b) Track length estimation.

5. CONCLUSION

By leveraging TR technique to exploit the CSI of a multipath channel, we propose TRITS that tracks the moving TD with centimeter accuracy in real time. Based on the concept of logical locations and the spatial distribution of TRRS, each location on a moving trajectory can be identified and the moving speed can be estimated. Because of its high accuracy, low complexity and small latency, TRITS is a prominent solution to future indoor tracking applications with fixed paths.

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