

Fingerprint-Based mmWave Positioning System Aided by Reconfigurable Intelligent Surface

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Abstract—Reconfigurable intelligent surface (RIS) is a promising technique for millimeter wave (mmWave) positioning systems. In this letter, we consider multiple mobile users (MUs) positioning problem in the multiple-input multiple-output (MIMO) time-division duplex (TDD) mmWave systems aided by the RIS. We derive the expression for the space-time channel response vector (STCRV) as a novel type of fingerprint. The STCRV fingerprint comprises the channel characteristics of the cascaded channel, such as the angle of arrival (AOA) at the RIS and the time delay from the MU to the RIS, which are indicative of the position of the MU. To process the STCRV with more features, we propose a novel residual convolution network regression (RCNR) learning algorithm to output the estimated three-dimensional (3D) position of the MU with higher accuracy. Specifically, the RCNR learning algorithm includes a data processing block to process the input STCRV, a normal convolution block to extract the features of STCRV, four residual convolution blocks to further extract the features and protect the integrity of the features, and a regression block to estimate the 3D position. Extensive simulation results are also presented to demonstrate that the proposed RCNR learning algorithm outperforms the traditional convolution neural network (CNN).

Index Terms—Reconfigurable intelligent surface (RIS), intelligent reflecting surface, positioning, radio localization.

I. INTRODUCTION

LOCALIZATION-RELATED industries demand high levels of localization accuracy [1], e.g., mobile user sensing [2]. It is worth pointing out that prevalent global positioning system (GPS) localization accuracy, even in ideal conditions, is approximately 5 meters, which falls short of meeting the stringent requirements of location-sensitive applications. Hence, wireless positioning systems in the millimeter wave (mmWave) band were advocated by some researchers as a way to improve the positioning performance [3]. However,

due to the sensitivity of mmWave signals to blockages, high-precision positioning is difficult to maintain [4].

Reconfigurable intelligent surface (RIS) is an emerging technique for mmWave positioning systems with several advantages [5], [6], [7], [8], [9], [10]. First, the RIS can reconstruct a new line-of-sight (LoS) communication link if the direct link was blocked by obstacles [6]. Second, the RIS has lower hardware costs than the access point (AP) when they are deployed as a wireless positioning reference point [7]. Moreover, the RIS provides reliable and high-precision estimation performance with low energy consumption [8]. Finally, the large number of the reflecting elements of the RIS enable high-accuracy radio positioning parameter estimation [9]. Thus, wireless positioning algorithms aided by a RIS is a promising enabler for the sixth-generation (6G) wireless systems [10].

Currently, wireless positioning algorithms aided by the RIS have been studied by some researchers, including two-step positioning algorithms and fingerprint based algorithms [11], [12]. However, the two-step positioning algorithms depend on the channel parameters estimation, which require line-of-sight (LoS) measurement.

Without estimating the channel parameters, fingerprint based positioning algorithms directly predict the position by using the fingerprint (e.g., received signal strength information (RSSI)). For example, [12] regarded RSSI as a type of fingerprint to predict the MUs aided by the RIS. However, RSSI-based fingerprint localization algorithms may be unstable due to the fast fading fluctuation. Recently, some researchers proposed to use the channel state information (CSI) as the fingerprint, due to its potential to enhance the positioning accuracy compared with RSSI [13], [14], [15]. The authors of [13] proposed to use CSI as a type of fingerprint in a single input single output (SISO) Wi-Fi localization system. The angle delay channel power matrix CSI fingerprint was adopted in [14] in a massive multiple-input multiple-output (MIMO) orthogonal frequency-division multiplexing (OFDM) system to estimate the 2D position of the MU. The authors of [15] proposed a CSI-based 3D positioning method for the MIMO-OFDM system using a convolution neural network (CNN). However, due to the obstacles in indoor environment, the direct links between the MUs and the AP may be blocked. Hence, we investigate the scenarios where the RIS is used to reconstruct an alternative communication link between the MUs and the AP. Moreover, as the CSI fingerprint of the cascaded AP-RIS-MU channel contains more features than the other types of CSI fingerprint, we propose a novel residual convolution network regression (RCNR) learning algorithm to extract more features and protect the integrity of features.

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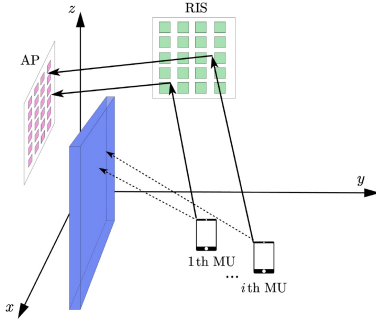


Fig. 1. RIS-aided positioning system model.

Against the above background, the main contributions of this letter are summarized as follows:

- 1) For the fingerprint based mmWave positioning system, we propose a new type of fingerprint, space-time channel response vector (STCRV), which consists of multipath channel characteristics. The STCRV has more features than the other types of CSI fingerprint, e.g., the AOA and the AOD at the RIS, and is closely related to the position of the MU. Moreover, the STCRV can be used as an alternative fingerprint for positioning when the direct link between the MU and the AP is blocked by obstacles.
- 2) Utilizing the STCRV as the wireless positioning fingerprint, we propose a novel RCNR learning algorithm to estimate the 3D positions of the MUs. The RCNR algorithm can be used to study the mapping between these channel characteristics and the position of the MU, thereby enabling precise localization. Specifically, STCRV is processed by a data processing block at first. Then, a normal convolution block is then used to extract the features of the output from the data processing block. Consequently, four residual convolution blocks are utilized to further extract more features caused by the cascaded AP-RIS-MU channel and protect the integrity. Finally, the 3D position is estimated through a regression block.
- 3) Simulation results are provided to evaluate the performance of the proposed STCRV fingerprint and the RCNR learning algorithm. The proposed algorithm outperforms the CNN and the WKNN in terms of cumulative distribution function (CDF).

II. SYSTEM MODEL AND PROBLEM FORMULATION

We consider an RIS-aided 3D massive multiple-input multiple-output (MIMO) time-division duplex (TDD) mmWave positioning system, where the MUs send pilot signals to the AP to locate the positions of the MUs aided by an RIS. In addition, we assume that the direct channels between the AP and the MUs are blocked by some obstacles, such as thick walls.

As we can see from Fig. 1, the AP is placed on the left side of the wall with the center located at $\mathbf{p} = [x_p, y_p, z_p]^T$. Moreover, the AP is assumed to be equipped with a uniform planar array (UPA) with $M_{x,z} = M_x \times M_z$ antennas, where M_x and M_z denote the numbers of antennas along the

x-axis and the z-axis, respectively. Additionally, the RIS is assumed to be placed at the front side of the wall with the center located at $\mathbf{s} = [x_s, y_s, z_s]^T$. The UPA-based RIS has $N_{y,z} = N_y \times N_z$ reflecting elements along the y-axis and the z-axis, respectively. Furthermore, there are N_u MUs, each of which is equipped with a single antenna. The MUs are located at $\mathbf{u}_i = [x_i, y_i, z_i]^T$, $i = 1, 2, \dots, N_u$.

It is assumed that the number of propagation paths between the i th MU and the RIS is N_p , the AOA of the p th path from the i th MU to the RIS can be decomposed into the elevation angle $0 \leq \theta_{p,i} \leq \pi$ in the vertical direction, and the azimuth angle $0 \leq \phi_{p,i} \leq \pi$ in the horizontal direction. As a result, the array response vector at the RIS can be expressed as [16]

$$\mathbf{a}_{R_a}(\theta_{p,i}, \phi_{p,i}) = \mathbf{a}_{R_a}^{(e)}(\theta_{p,i}) \otimes \mathbf{a}_{R_a}^{(a)}(\theta_{p,i}, \phi_{p,i}), \quad (1)$$

where $\otimes$ denotes the Kronecker product. Moreover, we have

$$\mathbf{a}_{R_a}^{(e)}(\theta_{p,i}) = \left[1, e^{\frac{-j2\pi d_r \cos \theta_{p,i}}{\lambda_c}}, \dots, e^{\frac{-j2\pi(N_y-1)d_r \cos \theta_{p,i}}{\lambda_c}} \right]^T, \quad (2)$$

and

$$\mathbf{a}_{R_a}^{(a)}(\theta_{p,i}, \phi_{p,i}) = \left[1, e^{\frac{-j2\pi d_r \sin \theta_{p,i} \cos \phi_{p,i}}{\lambda_c}}, \dots, e^{\frac{-j2\pi(N_z-1)d_r \sin \theta_{p,i} \cos \phi_{p,i}}{\lambda_c}} \right]^T, \quad (3)$$

where d_r and λ_c denote the distance between the adjacent elements of the RIS and the carrier wavelength, respectively. Then, the channel from the i th MU to the RIS, denoted as $\mathbf{g}_i$, can be modeled as

$$\mathbf{g}_i = \sum_{p=1}^{N_p} \alpha_{p,i} \mathbf{a}_{R_a}(\theta_{p,i}, \phi_{p,i}), \quad (4)$$

where $\alpha_{p,i}$ denotes the complex channel gain of the p th path.

Similarly, it is assumed that the number of propagation paths between the AP and the RIS is N_j . The angle of departure (AOD) of the j th path from the RIS to the AP can be decomposed into the elevation angle $0 \leq \theta_j \leq \pi$ in the vertical direction and the azimuth angle $0 \leq \phi_j \leq \pi$ in the horizontal direction. Hence, the array response vector can be expressed as $\mathbf{a}_{R_d}(\theta_j, \phi_j)$, which is similar to the expression of $\mathbf{a}_{R_a}(\theta_{p,i}, \phi_{p,i})$ in (1).

For the RIS-AP link, the AOA of the j th path can be decomposed into the elevation angle $0 \leq \psi_j \leq \pi$ in the vertical direction and the azimuth angle $0 \leq \omega_j \leq \pi$ in the horizontal direction. Therefore, the array response vector $\mathbf{a}_B(\psi_j, \omega_j)$ can be written as

$$\mathbf{a}_B(\psi_j, \omega_j) = \mathbf{a}_B^{(e)}(\psi_j) \otimes \mathbf{a}_B^{(a)}(\psi_j, \omega_j), \quad (5)$$

with

$$\mathbf{a}_B^{(e)}(\psi_j) = \left[1, e^{\frac{-j2\pi d_b \cos \psi_j}{\lambda_c}}, \dots, e^{\frac{-j2\pi(M_z-1)d_b \cos \psi_j}{\lambda_c}} \right]^T, \quad (6)$$

and

$$\mathbf{a}_B^{(a)}(\psi_j, \omega_j) = \left[1, e^{\frac{-j2\pi d_b \sin \psi_j \cos \omega_j}{\lambda_c}}, \dots, e^{\frac{-j2\pi(M_x-1)d_b \sin \psi_j \cos \omega_j}{\lambda_c}} \right]^T, \quad (7)$$

where d_b is the antenna spacing at the AP.

By using the array response vector $\mathbf{a}_{R_d}(\theta_j, \phi_j)$ and $\mathbf{a}_B(\psi_j, \omega_j)$, the channel matrix of the AP with the RIS can be formulated as

$$\mathbf{H} = \sum_{j=1}^{N_j} \beta_j \mathbf{a}_B(\theta_j, \phi_j) \mathbf{a}_{R_d}^H(\psi_j, \omega_j), \quad (8)$$

where β_j denotes the channel gain of the j th path.

Denote $\Psi_t \in \mathbb{C}^{N_{y,z} \times N_{y,z}}$ as the phase shift matrix of the RIS in time slot t . It is assumed that the MUs transmit pilot sequences of length τ via the RIS to the AP. During the uplink transmission of the i th MU, in time slot t , $1 \leq t \leq \tau$, the received signal from the i th MU at the AP can be written as

$$\mathbf{y}_i(t) = \mathbf{H} \Psi_t \mathbf{g}_i \sqrt{p} s_i(t) + \mathbf{n}_i(t), \quad (9)$$

where $s_i(t)$ denotes the pilot signal from the i th MU, $\mathbf{n}_i(t) \in \mathbb{C}^{M_{x,z} \times 1} \sim \mathcal{CN}(0, \delta^2 \mathbf{I})$ represents additive white Gaussian noise (AWGN) with power δ^2 at the AP. Here, p denotes the transmit power of the i th MU. According to the expression of the received signal from the i th MU, we can define the space-time channel response vector (STCRV) of the i th MU as

$$\mathbf{h}_i = \mathbf{H} \Psi_t \mathbf{g}_i, \quad (10)$$

which consists of the channel parameters (e.g., channel gain and AOA/AOD). The STCRVs are unique for different positions, hence the STCRVs can be regarded as a new type of CSI fingerprint of the MU. According to the definition of directly positioning algorithms [15], the STCRVs can be used to estimate the positions of the MUs. Therefore, by denoting the estimated position of the i th MU as $\hat{\mathbf{u}}_i = [\hat{x}_i, \hat{y}_i, \hat{z}_i]^T$, we have

$$\hat{\mathbf{u}}_i = f(\mathbf{h}_i), \quad (11)$$

where $f(\cdot)$ denotes the complex non-linear function between the STCRV and the estimated position of the i th MU. Hence, the regression problem of estimating the positions of the MUs can be formulated as

$$\min_{\hat{\mathbf{u}}_i} \frac{1}{N_u} \sum_{i=1, \dots, N_u} (\hat{\mathbf{u}}_i - \mathbf{u}_i)^2. \quad (12)$$

III. RESIDUAL CONVOLUTION NETWORK REGRESSION LEARNING ALGORITHM

According to the regression problem in (12), the closed-form expression of the 3D position of the MU is not available by using traditional optimization methods. Hence, a regression learning algorithm to predict the positions of MUs is developed in this section. Deep learning based method, popular in image recognition of computer science, can be applied to the STCRV fingerprint positioning since the STCRV can be seen as an image. Therefore, we propose a novel residual convolution network regression (RCNR) learning algorithm to represent the function $f(\cdot)$ in (11) and solve the regression problem (12).

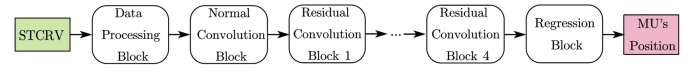


Fig. 2. The structure of the residual convolution network regression (RCNR) learning algorithm.

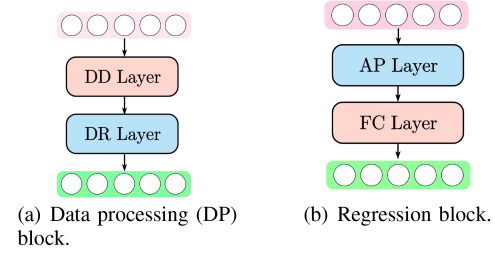


Fig. 3. Two blocks used for the proposed algorithm.

A. Regression-Oriented Positioning

In computer science, convolution neural network (CNN) is often used for image classification with the last layer being activated by a softmax function [17]. As an alternative to the classification function, CNN can also be viewed as a regression function if the softmax layer is replaced by a fully connected layer containing an activation function. As an advanced network of CNN, residual convolution network (RCN) can also be used as regression function by substituting a fully connected layer into the last softmax layer.

B. The Structure of the RCNR Learning Algorithm

Fig. 2 shows the details of the proposed algorithm. As shown in Fig. 2, the proposed algorithm consists of a data processing block, a normal convolution block, four residual convolution blocks, and a regression block. The descriptions of these blocks will be introduced as follows.

1) *Data Processing Block*: The data processing (DP) block is designed to process the input STCRV. As we can see from Fig. 3(a), the DP block includes two layers: a data decomposing (DD) layer, and a data reshape (DR) layer.

First, since the STCRV is a complex vector, we design the DD layer to decompose $\mathbf{h}_i$ into two parts, the real value vector $\mathbf{h}_i^{(r)}$ and the imaginary value vector $\mathbf{h}_i^{(i)}$, which can be expressed as

$$\mathbf{h}_i = \mathbf{h}_i^{(r)} + j\mathbf{h}_i^{(i)}. \quad (13)$$

Then, according to the expression of the STCRV in (10), the STCRV consists of the features of the horizontal angle domain and the vertical angle domain of the AP. To further extract these features, we design the DR layer to reshape the two vectors $\mathbf{h}_i^{(r)} \in \mathbb{C}^{M_{x,z} \times 1}$ and $\mathbf{h}_i^{(i)} \in \mathbb{C}^{M_{x,z} \times 1}$ as two space-time channel response matrices (STCRM), which are denoted as $\mathbf{H}_i^{(r)} \in \mathbb{C}^{M_x \times M_z}$ and $\mathbf{H}_i^{(i)} \in \mathbb{C}^{M_x \times M_z}$, respectively. To be specific, we reshape these two vectors by arranging the elements of vector into M_x rows and M_z columns.

2) *Normal Convolution Block*: The normal convolution (NC) block is designed to extract the features of the STCRM. As we can see from Fig. 4(a), the NC block consists of three layers: a convolution (Con) layer, a batch normalization (BN) layer, and a max pooling (MP) layer.

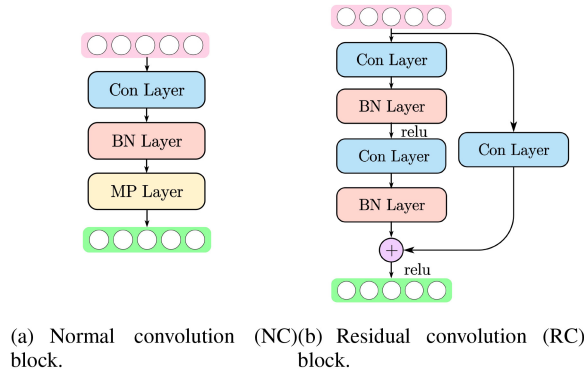


Fig. 4. Two kinds of convolution block used for the proposed algorithm.

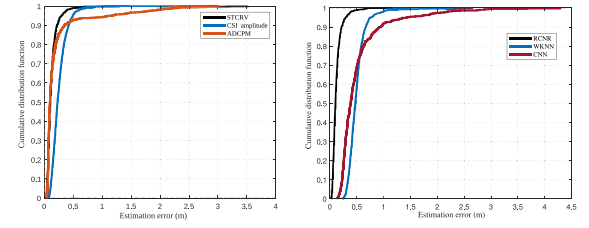
Due to the large number of antennas at the AP, the STCRM has a large dimension. Therefore, if the STCRM is input directly into a deep neural network (DNN) consisting of fully connected layers, a large number of weight parameters of the DNN should be trained. To improve the efficiency of the training neural network, the Con layer is proposed [17]. The Con layer has multiple filters sliding over it for a given input STCRM so that the features of STCRM can be extracted [17]. As a result, the number of weight parameters to be trained can be reduced. Moreover, the BN layer is designed to normalize the input data so that the convergence rate can be improved. Furthermore, the MP layer is designed to reduce the complexity of further layers, which is similar to reducing the resolution in the field of computer science.

3) *Residual Convolution Block*: In the field of computer science, increasing the number of the Con layers will allow the neural network to extract more features [17]. However, according to the experiment in [18], when the neural network reaches a certain depth, the problem of gradient explosion and gradient disappearance will appear, which leads to a worse optimization effect and lower accuracy of the proposed neural network. Hence, to improve the estimation accuracy, the residual convolution network is proposed to enable the deeper neural network to train well and obtain a better optimization effect [18].

As the considered STCRV is the CSI that consists of the cascaded AP-RIS-MU channel. Hence, the STCRV contains more features than the other types of CSI fingerprint. Inspired by the residual convolution network of computer science, the residual convolution (RC) block is designed to further extract the features of STCRV and protect the integrity of features in our proposed RCNR learning algorithm. As shown in Fig. 4-(b), the RC block includes three Con layers and two BN layers.

As we can see from Fig. 4-(b), the RC block starts with two Con layers. Each Con layer is followed by a BN layer and a ReLU activation function. Then we skip these 2 convolutional operations through the cross-layer datapath and add the input directly before the final ReLU activation function. As a result, the integrity of the features is protected and the degradation of the neural network can be solved.

4) *Regression Block*: The regression block is designed to output the estimated positions of the MUs. As shown in Fig. 3-(b), the regression block includes an average pooling (AP) layer and a fully connected (FC) layer.



(a) The CDF of estimation error with different fingerprints. (b) The CDF of estimation error with different algorithms.

Fig. 5. The CDF of estimation error.

The AP layer is used to reshape the output of the RC blocks for the final FC layer by taking the average of each feature from the RC block [17]. Adding the AP layer between the RC block and the FC layer avoids the large number of weight parameters introduced by the FC layer. As a result, the AP layer reduces overfitting while improving the convergence rate.

The FC layer is used to combine the features from the NC blocks and output the estimated positions of the MUs. The FC layer multiplies the input by a parametric weight matrix and then adds a bias vector. By using Ω to denote the output before the FC layer, the estimated position after the FC layer can be written as

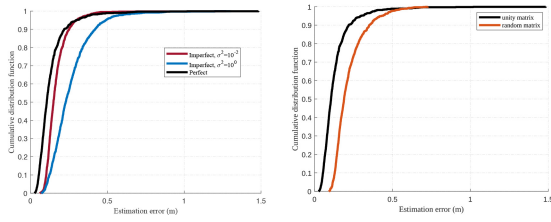
$$\hat{\mathbf{u}}_i = \mathbf{W} \text{vec}\{\Omega\} + \mathbf{b}, \quad (14)$$

where $\mathbf{W}$ and $\mathbf{b}$ are the parametric weight matrix and bias vector respectively that can be learned together with the training of the RCNR learning algorithm.

IV. SIMULATION RESULTS

In this section, simulation results are provided to evaluate the performance of the proposed RCNR algorithm. The software Wireless Insite [19] is used to simulate the mmWave positioning system aided by the RIS. The carrier frequency is $f = 90$ GHz. For the AP, the number of antennas is set to $M_{x,z} = M_x \times M_z = 255 \times 255$. Besides, the center of the AP is located at $\mathbf{p} = (-10, -5, 2.5)$ m, and the distance between the antennas d_b is set to $d_b = \lambda/2 = 1.67 \times 10^{-3}$ m. For the RIS, the number of the elements is set to $N_{y,z} = N_y \times N_z = 255 \times 255$. Moreover, the center of the RIS is located at $\mathbf{s} = (-5.10, -1.43, 2)$ m and the distance of the elements is set to $d_r = \lambda/2 = 1.67 \times 10^{-3}$ m. For the MUs, we assume that the MUs are uniformly distributed in the grid of 9.6 m in length and 5.8 m in width. Furthermore, we have set up three grids in total, and the heights of the grids are 1.4 m, 1.5 m, and 1.6 m, respectively. In addition, the distance of the MUs is 0.2 m and the transmit power of the MUs is 10 dBm. The phase shifts of the elements at the RIS are set to a unity matrix.

To demonstrate the superiority of the proposed STCRV fingerprint, we compare it with two benchmarks, namely the CSI amplitude in [13] and the angle delay channel power matrix (ADCPM) in [15]. As illustrated in Fig. 5-(a), the results show that when the STCRV fingerprint is used as the dataset, the proposed RCNR algorithm achieves the highest positioning accuracy, with 90% of the estimation error within 0.25 m. In comparison, the CSI amplitude



(a) The CDF of estimation error with different kinds of CSI error. (b) The CDF of estimation error with different phase shift matrices.

Fig. 6. The CDF of estimation error.

fingerprint and the ADCPM fingerprint have lower estimation accuracy, with 50% and 82% accuracy, respectively. Therefore, Fig. 5-(a) clearly demonstrates the superiority of the proposed STCRV fingerprint.

To evaluate the performance of the proposed RCNR algorithm, we present the estimation error CDF comparison of the RCNR algorithm, CNN algorithm in [13], and WKNN algorithm in [14]. As shown in Fig. 5-(b), when we use the proposed RCNR algorithm, the estimation error at the 90% point is 0.25 m. However the estimation errors at the 90% point are 0.7 m and 0.9 m for the WKNN algorithm and the CNN algorithm, respectively. It means that the proposed RCNR algorithm outperforms the WKNN and the CNN algorithm.

To investigate the impact of the CSI estimation error on the considered systems and the algorithm, we evaluate the performance versus different CSI estimation conditions in Fig. 6(a). We assume that the estimation error of the STCRV is i.i.d. complex Gaussian random variable with zero-mean and variance σ^2 . The estimation errors at 90% are 0.25 m, 0.3 m, and 0.45 m for $\sigma^2 = 0$, $\sigma^2 = 10^{-2}$, and $\sigma^2 = 10^{-1}$. It implies that the CSI estimation error degrades the estimation accuracy.

Moreover, we study the impact of the phase shift matrix on the performance of the proposed system and algorithm in Fig. 6-(b). As illustrated in Fig. 6-(b), the estimation error at the 90% point is 0.25 m for the RIS with a unity matrix, whereas it increases to 0.35 m for the random matrix. The simulation results suggest that the proposed system and algorithm are sensitive to the choice of the phase shift matrix of the RIS.

Remark: In this letter, a unity matrix is assumed for the scenario that the RIS is located at the center of an indoor environment with symmetrical areas on both sides where the MUs need to be located. However, exploring the optimal phase shift for other scenarios in the RIS-assisted localization system would be an interesting future work.

V. CONCLUSION

In this letter, we studied the MU positioning problem in MIMO TDD mmWave systems aided by the RIS. We derived

the expression for STCRV at the AP as a new type of fingerprint. In addition, by using the STCRV fingerprint as input, we proposed a novel RCNR algorithm to predict the 3D position of the MU. Extensive simulation results were presented to demonstrate the superiority of the proposed RCNR algorithm.

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