

MUSIC Spectrum Based Interference Detection and Localization for mmWave RIS-MIMO System

Yafei Hou^{*†}, Kazuto Yano^{*}, Narisato Suga^{*‡}, Satoshi Denno[†], Toshikazu Sakano^{*}

^{*}Wave Engineering Laboratory, ATR International, Kyoto, Japan

[†]Graduate School of Natural Science and Technology, Okayama University, Okayama, Japan

[‡]Dept. of Information and Communications Engineering, Shibaura Institute of Technology, Tokyo, Japan

Contact Author: yfhou@okayama-u.ac.jp

Abstract—For millimeter wave (mmWave) MIMO system, the capacity can be largely improved using beamforming technology if the system can detect the interference signal and its location. This paper proposes a Multiple Signal Classification (MUSIC) spectrum based method to detect an interference occurrence and find the location of the interference source for mmWave reconfigurable intelligent surface (RIS)-MIMO system. The MUSIC method can estimate the arrival of angles (AoAs) from the available auto-correlation of the received signal by searching for peaks in the MUSIC spectrum. Therefore, MUSIC spectrum can be treated as the ‘signature’ of the transmit signals from different locations. This paper utilizes this property to detect the interference occurrence and find the interference location for RIS-MIMO system in a low-complexity way.

I. INTRODUCTION

Millimeter (mm) wave multiple-input and multiple-output (MIMO) system is considered to be one of most major technologies for 5G wireless networks [1]. Due to short wavelength, mmWave MIMO system can employ an antenna array with a large number of antennas, which significantly enhances the capacity of the system for supporting large users [2]. In addition, mmWave system can use the vast spectrums in the mmWave band (30~300 GHz) to achieve up to 100 times increase in transmission rate over current systems [3] which further facilitates the realization of novel applications for 5G/6G era, such as Wireless HD, V2V/V2I Communication, WiGig, Medicare etc [4]. Therefore, many new methods and antenna technologies are employed to further improve the capacity of mmWave MIMO system.

One of important research topics for mmWave MIMO system is how to reduce the co-channel interference of undesired users. This topic can be simplified as the interference detection and prediction of interference arrival. The interference detection [5] aims to check out whether the received signal includes the signal of undesired users and find their correct locations or directions if interference exists. The prediction of interference arrival attempts to know the coming timing of interference occurrence and its transmission pattern or duration based on the collected information [6]. These researches are very important for mmWave MIMO system. Firstly, if the location or direction of interference sources can be correctly captured, the beamforming technique can suppress or alleviate the interfering signals by steering nulls of the pattern in the direction of interference sources without affecting the main

beam. For mmWave massive MIMO system, the more accurate location information the transmitter has, the more improvement of capacity it can achieve. On the other hand, with the known transmission pattern or duration of the interference, the transmitter can schedule its beamforming patterns to avoid its capacity loss.

There are many research directions of interference detection. In [7], the authors developed a lightweight method targeting interference identification using real-time extraction of envelope and model-aided spectral features for the IEEE 802.11b/g/n, 802.15.4, 802.15.1, or Bluetooth Low Energy wireless system. The authors in [8, 9] proposed an inverter microwave oven (MWO) signal detection method in the time and frequency domains for reliable wireless communication using the experimental MWO data obtained in a shielded room. It is revealed that the proposed method is able to detect the inverter MWO signal correctly and is robust against different products, different receiving environment, and presence of other signals. Some researches focus on the coexistence between IEEE 802.11 wireless local area network (WLAN) and radars operating in co/adjacent channel scenarios [10]. The authors proposed the modified receiver which includes a new inter-leaver and a log-likelihood ratio (LLR) mapping function to mitigate the impact of radar interference. In our paper [11], we proposed a methodology for classifying increasing severity and types of interference to improve throughput prediction using received signal strength (RSS) data which collected from both a ray-tracing simulation and the measurement campaign. By using the scalogram time-frequency images computed from the RSS signal and a convolutional neural network (CNN), the spectral features and interference classification can be correctly classified on over 65% of the occasions.

In addition, recently, a new and powerful low-cost reconfigurable intelligent surface (RIS) becomes a hot topic. RIS includes massive unit cells and each unit cell can adjust the reflected waves of radio signals to desired directions without or with a few RF chains. This novel RIS antenna technique can configure a smart radio environment (SRE) for the capacity enhancement of many wireless technology [12]. It can be installed at many places such as at wall/roof of room, building, interior of vehicular, etc. Due to many merits of using RIS, many new research projects and topics appeared in recent years especially over mmWave band where one RIS can be

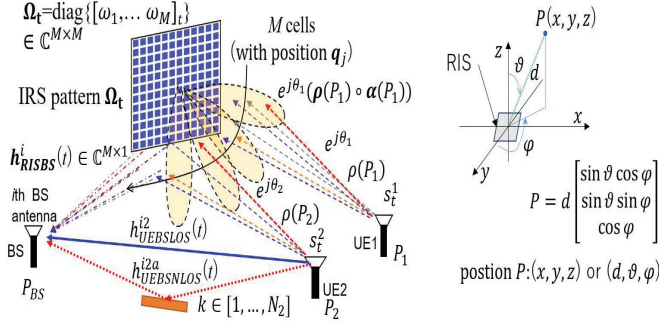


Fig. 1. The channel model of mmWave RIS-MIMO communication system.

integrated with more cells.

In this paper, we propose a Multiple Signal Classification (MUSIC) spectrum based method to detect an interference occurrence and find the interference location for mmWave RIS-MIMO system. Usually, the auto-correlation process on the received signal at a receiver with uniform linear array (ULA) can be used for detecting the arrival of angles (AoAs) from transmitters for planar wave system [13]. The MUSIC method can estimate the noise subspace from the available auto-correlation of the received signal and searches for steering vectors that are as orthogonal to the noise subspace as possible. The AoAs estimation is normally accomplished by searching for peaks in the MUSIC spectrum. Therefore, MUSIC spectrum can be treated as the ‘signature’ of the transmit signals from different locations. We will utilize the MUSIC spectrum to detect the interference occurrence and find the interference location with different RIS patterns.

This paper is organized as follows. Section II describes the model of mmWave RIS-MIMO system. Then the proposed MUSIC spectrum based interference detection is explained in Section III. Then the simulated results of proposed method are shown in Section IV. The paper ends with conclusions presented in Section V.

II. THE CHANNEL MODEL OF MMWAVE RIS-MIMO COMMUNICATION SYSTEM

Figure 1 shows the channel model of a mmWave RIS-MIMO communication system assumed in this paper. Here we assume that BS and UE have \$K\$ and \$L\$ antennas. The RIS which includes \$M\$ cells is assumed that each cell can reflect input wave to any directions in this paper, and the RIS pattern is represented as \$\Omega_t\$ with \$[\omega_{t,1}, \dots, \omega_{t,M}]\$. We use \$P_m\$ to represent the location of the \$m\$-th UE. For mmWave system over indoor scenarios, usually, the channel model can be simulated using a spherical wave model with \$(d, \vartheta, \varphi)\$ as shown in the right side of the figure. Here \$d\$ represents the distance between the UE and the RIS. The AoAs \$\vartheta \in [0, \pi/2]\$ and \$\varphi \in [0, 2\pi]\$ are the angle between the Z-axis and the angle between the projection of \$P_m\$ on the XY plane and the X-axis, respectively. Therefore, the wave-vector as a function of \$\vartheta\$ and

\$\varphi\$ can be given as

$$\kappa(\vartheta, \varphi) = -\frac{2\pi}{\lambda} \begin{bmatrix} \sin \vartheta \cos \varphi \\ \sin \vartheta \sin \varphi \\ \cos \vartheta \end{bmatrix}. \quad (1)$$

It can be used to represent the position vector as \$\mathbf{p} = -\lambda d \kappa(\vartheta, \varphi) / 2\pi\$ with \$d = \|\mathbf{p}\|\$.

The wireless channel between the \$m\$-th transmitter antenna with a symbol \$s_t^m\$ and \$i\$-receiver antenna including one RIS device can be represented as

$$y_i(t) = \sum_{m=1}^L \left\{ (\mathbf{h}_{RISBS}^i)^T e^{j\theta_m} \Omega_t(\rho(P_m) \circ \alpha(P_m))(t) + \mathbf{h}_{UEBSLOS}^{im}(t) + \sum_{a=1}^N \mathbf{h}_{UEBSNLOS}^{ima}(t) \right\} s_t^m + n^i(t). \quad (2)$$

Operator \$\circ\$ here is the point-wise product of vectors. \$\rho(P_m) \leq \mathbf{0}_M\$ is the vector with amplitudes of wireless channels among the RIS elements and the transmitter, and \$\alpha(P_m) \in \mathbb{C}^{M \times 1}\$ is the vector of channel phases. Here the superscripts \$[\cdot]^T\$ represents the transpose of its argument. \$\theta_m\$ is the phase between the transmitter and origin of RIS as \$d_m/\lambda\$. \$\rho(P_m) \circ \alpha(P_m) \in \mathbb{C}^{M \times 1}\$ is the vector of complexity values related to the place of the RIS device. \$\mathbf{h}_{RISBS}^i(t)\$ represents the channel between the RIS and the \$i\$-th receiver antenna. \$\mathbf{h}_{UEBSLOS}^{im}(t)\$ and \$s_t^m\$ are the direct wave or line-of-sight and transmitted symbol between the \$m\$-th transmitter antenna and the \$i\$-th receiver antenna. \$\mathbf{h}_{UEBSNLOS}^{ima}(t)\$ is the \$a\$-th reflected wave of \$N\$ reflected waves between the \$m\$-th transmitter antenna and the \$i\$-th receiver antenna. \$n^i(t)\$ is the zero-mean additive Gaussian noise with variance \$N_0/2\$ at the \$i\$-th receiver antenna.

The channel models for \$\mathbf{h}_{RISBS}^i\$ and \$\rho(P_m) \circ \alpha(P_m)\$ can be further represented under the plane-wave model for far-field (Fraunhofer region) where the distance between the transmitter and RIS or receiver is larger than Rayleigh distance expressed by \$2D^2/\lambda\$ with \$D\$ as the aperture of radiation. If the distance is smaller than Rayleigh distance, the channel model should be treated as near-field one with spherical-wave model. For mmWave system, due to short wavelength, channel models over indoor cases are usually selected with near-field one.

The channel model of RIS [14] for far-field can be represented as

$$\rho(P) = \rho \mathbf{1}_M, \quad [\alpha(P)]_i = \exp(-j\mathbf{q}_i^T \kappa(\vartheta, \varphi)) \quad (3)$$

where \$\rho^2 = f(\vartheta, \varphi) \frac{A \cos \vartheta}{4\pi d^2}\$, \$\mathbf{q}_i\$ is the center location of \$i\$-th cell, and \$A\$ is the size of RIS element. \$f(\vartheta, \varphi)\$ is a correction factor as \$1 - \sin^2(\vartheta) \sin^2(\varphi)\$. It should be noted that the power loss model is assumed to be related with \$d^{-2}\$ in the equation (3), however it can be revised according to the different power loss model over different frequency band.

The RIS channel model for near-field can be represented as

$$\rho(P) = \rho \mathbf{1}_M, \quad [\alpha(P)]_i = \exp(-j\frac{2\pi}{\lambda} (\|p - \mathbf{q}_i\| - d)) \quad (4)$$

When \$d \gg \|\mathbf{q}_i\|, \forall i\$, the channel model reverts to that of far-field one.

III. MUSIC SPECTRUM BASED INTERFERENCE DETECTION AND LOCALIZATION

There are many AoA estimation methods especially for the far-field case where the plane-wave model can be used for method design. One popular method is the MUSIC method [15] using the matrix decomposition to find the eigenvalues and eigenvectors of the auto-correlation matrix of the received signal. Then by searching the steering vectors that are as orthogonal to the noise subspace as possible, the AoAs estimation can be inferred using the steering vectors which are also called as MUSIC spectrum.

From Eq. (1), we can use one simplified equation to show the received signal related to AoAs (ϑ_m, φ_m) as followings

$$y_i(t) = \sum_{m=1}^L f_m^i(\vartheta_m, \varphi_m) s_t^m(t) + n^i(t). \quad (5)$$

It should be noted that above equation only considers the case of one UE. It can be easily changed for the case of multiple UEs.

Suppose the samples are received at all K receiver antennas and are represented as

$$\mathbf{y}_t = \mathbf{A} \mathbf{s}_t + \mathbf{n}_t \quad (6)$$

where $\mathbf{A}$ is $[\mathbf{j}(\vartheta_1, \varphi_1), \dots, \mathbf{j}(\vartheta_m, \varphi_m)]$ and $\mathbf{j}(\vartheta_m, \varphi_m) = [f_m^1(\vartheta_m, \varphi_m), \dots, f_m^K(\vartheta_m, \varphi_m)]^T$. $\mathbf{s}_t$ is $[s_t^1, \dots, s_t^L]^T$ and $\mathbf{n}_t$ is $[n_t^1, \dots, n_t^K]^T$. Therefore, the auto-correlation of received signal can be represented as

$$\mathcal{R}_{yy} = \mathbb{E}\{\mathbf{y}_t \mathbf{y}_t^H\} = \mathbf{A} \mathbb{E}\{\mathbf{s}_t \mathbf{s}_t^H\} \mathbf{A}^H + \sigma_n^2 \mathbf{I}. \quad (7)$$

Here superscript $[\cdot]^H$ and $\mathbb{E}$ represent the conjugate transpose of its argument and average operator, respectively.

The MUSIC spectrum can be obtained by operating the eigenvalue decomposition on the auto-correlation matrix $\mathcal{R}_{yy}$. Let us assume that $\mathbf{s}_t \mathbf{s}_t^H$ can be a unit power matrix as $\mathbf{I}$, the Eq. (7) can be represented as

$$\mathcal{R}_{yy} \mathbf{e}_i = (\mathbf{A} \mathbb{E}\{\mathbf{s}_t \mathbf{s}_t^H\} \mathbf{A}^H + \sigma_n^2 \mathbf{I}) \mathbf{e}_i = (\mu_i + \sigma_n^2) \mathbf{e}_i = \lambda_i \mathbf{e}_i, \quad (8)$$

where λ_i and $\mathbf{e}_i$ are eigenvalue and its corresponding eigenvector of the matrix $\mathcal{R}_{yy}$. In addition, the eigenvalues have the property as

$$\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_L \geq \lambda_{L+1} = \dots = \lambda_K = \sigma_n^2. \quad (9)$$

The $(K - L)$ eigenvectors $(\mathbf{e}_{L+1}, \dots, \mathbf{e}_K)$ related to eigenvalues $(\lambda_{L+1}, \dots, \lambda_K)$ with value σ_n^2 can be used for configuring a noise subspace of $\mathcal{R}_{yy}$.

The MUSIC based AoA estimation method searches the MUSIC spectrums $P(\vartheta, \varphi)$ that are as orthogonal to the noise subspace as possible which is represented as

$$P(\vartheta, \varphi) = \frac{\mathbf{J}^H(\vartheta, \varphi) \mathbf{J}(\vartheta, \varphi)}{\mathbf{J}^H(\vartheta, \varphi) \mathbf{E}_N \mathbf{J}(\vartheta, \varphi)}, \quad (10)$$

where $\mathbf{E}_N = [\mathbf{e}_{L+1}, \dots, \mathbf{e}_K]$. the MUSIC based AoA estimation needs to find L peak values over $P(\vartheta, \varphi)$ by trying each combination of (ϑ, φ) which needs huge computational

complexity (CC) especially when considering multiple UEs and reflected waves over spherical wave space.

MUSIC-based AoA estimation has been largely used for channel model over the far-field case where most waves can be treated as plane wave with only unknown AoAs ϑ . In such case, the computational complexity of estimation will be reduced. On the other hand, to estimate all AoAs, the noise subspace needs to be included more eigenvectors. It has to increase the number of antennas of ULA. On the other hand, due to the reflected waves from scatters and RIS, the AoAs at receiver side appear more complicated distribution and properties. Finding extremely accurate AoAs over mmWave channels is difficult with more antennas and computational resources.

However, for interference detection, it needs not to find the extremely accurate AoAs. MUSIC spectrum can be treated as the ‘signature’ of the transmit signals from different locations and can be used as the indicator on that the interference signal appears or not. On the other hand, by collecting the MUSIC spectrums as finger printer (FP) of some pre-selected locations, the received MUSIC spectrum including interference signal can be used to coarsely detect the location of the interference source.

The proposed MUSIC spectrum based interference detection includes two steps. Firstly, several MUSIC spectrums without interference occurrence are generated as the fingerprint samples. The minimum correlation value of these fingerprint samples can be used as the threshold for interference detection. Then the interference detection only compares the correlation values between the MUSIC spectrum $P_{new}(\vartheta)$ for detection and N_S fingerprint samples $P_{FP}^i(\vartheta)$, $(i = 1, \dots, N_S)$. The interference occurrence can be decided using the criterion as

$$\begin{aligned} \exists i \in [1, \dots, N_S], \text{Cor}(P_{new}(\vartheta), P_{FP}^i(\vartheta)) &\geq \rho_{Thes} \\ &\Rightarrow \text{Without interference} \end{aligned} \quad (11)$$

$$\begin{aligned} \forall i \in [1, \dots, N_S], \text{Cor}(P_{new}(\vartheta), P_{FP}^i(\vartheta)) &< \rho_{Thes} \\ &\Rightarrow \text{With interference} \end{aligned} \quad (12)$$

Using the similar way, the MUSIC spectrum based method can coarsely estimate the location of the interference source. The BS can divide the space into many small grids and select some known locations as interference sources to build the known MUSIC spectrums related to this selected locations as fingerprint samples. For the localization of the interference source randomly generated from unknown location, BS just calculates the correlation values between these known MUSIC spectrums and this new MUSIC spectrum intended for localization and find the maximum one. Then the location is decided with the selected position of the grid which has the maximum correlation value. Since the interference sources are randomly from the space, the method only coarsely detects the location of interference source.

Usually, for interference detection and localization, it is necessary to use the accurate channel status information (CSI) or AoAs. The proposed MUSIC spectrum based method just utilizes the received signal and does not require any CSI,

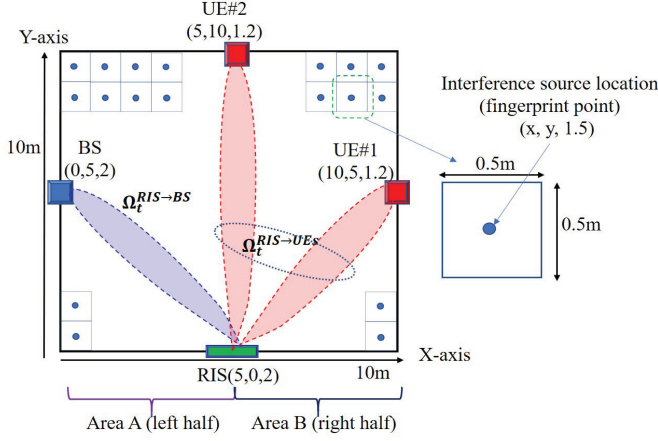


Fig. 2. The simulated scenarios.

AoAs between the BS, UE and RIS device. Therefore it largely reduces the computational complexity and resource for channel estimation. Of course, the localization accuracy of the proposed method is limited. However the proposed method can be further improved using machine learning, distributed BSs and adjustable RIS patterns.

IV. SIMULATION RESULTS

A. Simulated scenario and parameters

In this section, we simulate the performance of interference detection and localization using the proposed MUSIC spectrum based method. The simulated scenario is given in Fig. 2. One BS and two UEs are set at (0, 5 m, 2 m), (10 m, 5 m, 1.2 m) and (5 m, 10 m, 1.2 m), respectively. RIS is set with the origin points at (5 m, 0, 2 m) and its reflected surface faces to the Y-axis direction.

For the RIS pattern Ω_t , we have simulated two different cases. The first pattern ($\Omega_t^{RIS \rightarrow BS}$) makes the link power between the RIS cells and BS antennas as maximum as possible. This can be realized by grouping the cells to the number of BS antennas, and then the cells of each group set their reflected phases as the conjugate value of channel between the cells and the corresponding BS antenna [14]. The second pattern ($\Omega_t^{RIS \rightarrow UEs}$) is similar to that of the first one but makes the link power between the RIS cells and UE antennas as maximum as possible.

The simulated system parameters are listed in Table I. The signal of interference and UEs is generated using OFDM symbol with the IFFT size of 2048 and 1200 subcarriers. The MUSIC spectrum is generated using the data of one OFDM symbol. The path loss model of indoor case with LOS is listed as followings [16].

$$PL = 32.4 + 17.3 \log_{10}(d) + 20 \log_{10}(f_c) \quad [dB], \quad (13)$$

where f_c is frequency band with unit as [G Hz]. The RIS channel model is generated using the near-field one. The LOS path and NLOS paths are generated based on Ray-tracing

model which calculates the power and phase value using the link distance and Eq. (13). The scatter locations of NLOS paths are randomly generated within the indoor room.

The simulation runs 4000 times and randomly decides the interference occurs or not. Each time, if interference occurs, one additional interference signal is generated from an 1.5m-height interference transmitter with the location randomly generated from [0 m, 10 m] of both X-axis and Y-axis. Otherwise, the received signal only includes the signal of two UEs. In addition, we divided the indoor space into Area A (left half) and Area B (right half) to evaluate the impact of the distance between BS and UEs.

TABLE I
SPECIFICATIONS OF SIMULATION

Space size of indoor room	X:10m Y:10m Z(height):5m
Number of BS (ULA) (K) /UE antennas (L)	16 / 4 for two UEs
Spacing of BS/UE antennas	$\lambda/2$
Number of interference antennas	1
Center frequency band, bandwidth	60 GHz, 30.72 MHz
RIS cells (M), spacing	50×50, $\lambda/2$
transmit power (UEs, interference signal)	20 dBm
IFFT size, used sub-carriers /spacing	2048, 1200, 15kHz
Number of scatters (NLOS paths)	30
OFDM symbols per 1 ms	14

B. The simulated results of interference detection

Before the interference detection, the threshold value of minimum correlation value ρ_{Thes} needs to be decided. Based on the minimum correlation value of 100 times trial fingerprint samples, the threshold of interference detection ρ_{Thes} is set with 0.997 for the first RIS pattern ($\Omega_t^{RIS \rightarrow BS}$), and with 0.994 for the second RIS pattern ($\Omega_t^{RIS \rightarrow UEs}$), respectively.

The performance of interference detection is shown in Fig. 3 for the RIS pattern as $\Omega_t^{RIS \rightarrow BS}$, and in Fig. 4 for the RIS pattern as $\Omega_t^{RIS \rightarrow UEs}$, respectively. From both figures, when there is no interference, the proposed method can judge correct information with accuracy near to 100% when the FP samples N_S is increased to 10 because more FP samples increase the similarity of more MUSIC spectrums of the case without interference. On the other hand, when interference occurs, the accuracy is lightly reduced when N_S is increased to 10. It implies that further conditions are necessary in Eq. (12) to decide the occurrence of interference. In addition, when the interference signal from Area B, the detection accuracy is degraded little due to the large power loss of interference signal.

C. The simulated results of localization of interference source

To find the location of interference source, as shown in Fig. 2, we divide the X-Y plane into 441 grids with the size of 0.5 m × 0.5 m. For each grid, one interference source is located in the middle of grid as reference. Therefore, the BS has 441 kinds of known MUSIC spectrums as fingerprint samples as reference. The location is decided with the center position of the grid which has the maximum correlation value.

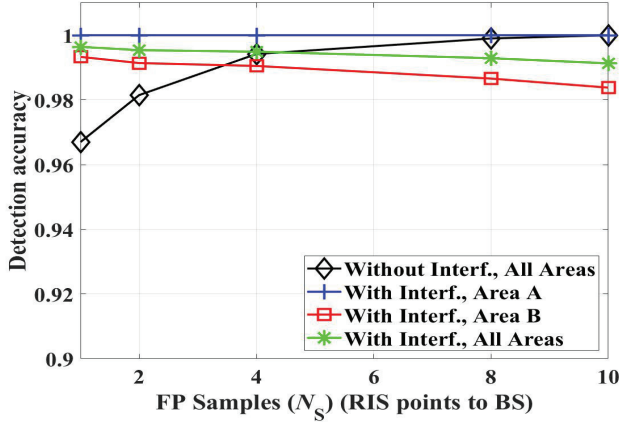


Fig. 3. The interference detection performance when the RIS pattern is $\Omega_t^{RIS \rightarrow BS}$.

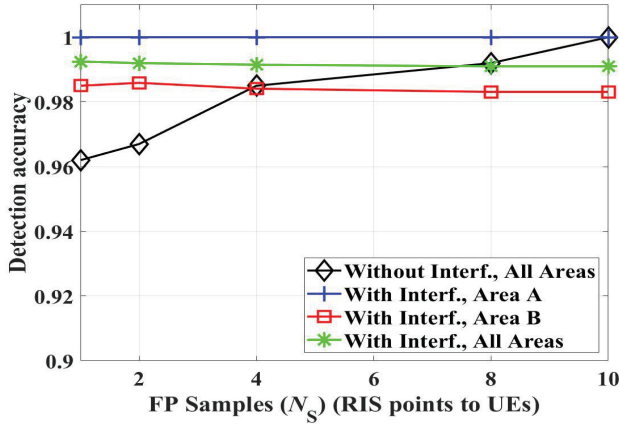


Fig. 4. The interference detection performance when the RIS pattern is $\Omega_t^{RIS \rightarrow UEs}$.

Since the interference sources are randomly from the X-Y plane, the method only coarsely detects the location of interference source.

The cumulative distribution function (CDF) results of the normalized localization error in X-axis and Y-axis are shown in Fig. 5 and Fig. 6 when the RIS pattern are $\Omega_t^{RIS \rightarrow BS}$ and $\Omega_t^{RIS \rightarrow UEs}$, respectively. The results show the proposed MUSIC spectrum based localization can provide the coarse location information of the interference source. In addition, the results also show that the localization accuracy of Y-axis is higher than that of X-axis. The reason comes from that the ULA of BS is parallel to the Y-axis which has large space resolution than that of X-axis. On the other hand, the RIS pattern seems to have not large impact on the localization performance in both figures. The main reason is that the RIS pattern only aims to change the link powers between the BS and UEs but not for the detection of interference source.

It should be noted that the proposed method is based on the fingerprint way which is sensitive to the change of

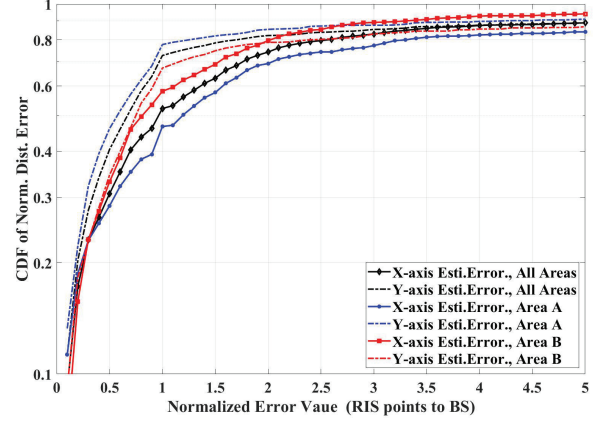


Fig. 5. The localization of interference source when the RIS pattern is $\Omega_t^{RIS \rightarrow BS}$.

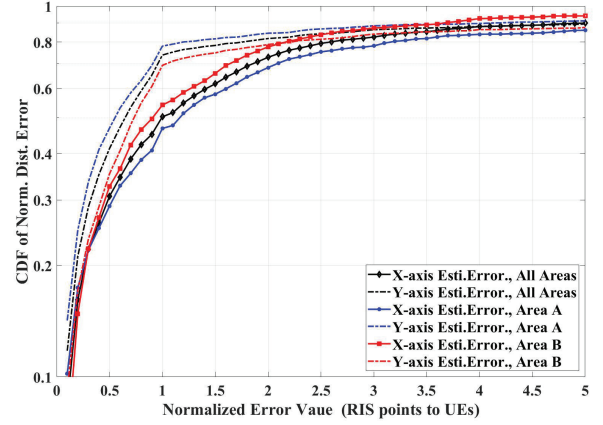


Fig. 6. The localization of interference source when the RIS pattern is $\Omega_t^{RIS \rightarrow UEs}$.

environments such as the increase or decrease of obstacles, adding some UEs. However, the proposed methods still works well if the signal of fingerprint at BS side has been fully updated according to the change of environments.

V. CONCLUSION

This paper has proposed a MUSIC spectrum based method to detect an interference occurrence and estimate the interference location for a mmWave RIS-MIMO system. The MUSIC spectrum can be used for AoAs estimation of the plane wave system over far-field scenarios. Therefore it is also treated as the ‘signature’ of the transmit signals from different locations. This property can be used for interference detection and localization of the interference source. Our simulated results confirmed that the interference detection can be accurately achieved with this method. In addition, the proposed method also can provide the coarse location information of the interference sources in a low-complexity way.

ACKNOWLEDGMENT

These research results were obtained from commissioned research (03401) by National Institute of Information and Communications Technology (NICT), JAPAN.

REFERENCES

- [1] M. Alsabah et al., “6G Wireless Communications Networks: A Comprehensive Survey,” *IEEE Access*, vol. 9, pp. 148191–148243, 2021.
- [2] E. Bjornson, L. Van der Perre, S. Buzzi and E. G. Larsson, “Massive MIMO in sub-6 GHz and mmWave: physical, practical, and use-Case differences,” *IEEE Wireless Communications*, vol. 26, no. 2, pp. 100–108, April 2019.
- [3] M. M. Azari et al., “Evolution of non-terrestrial networks from 5G to 6G: a survey,” *IEEE Communications Surveys & Tutorials*, vol. 24, no. 4, pp. 2633–2672, Fourthquarter 2022.
- [4] E. C. Strinati et al., “Reconfigurable, intelligent, and sustainable wireless environments for 6G smart connectivity,” *IEEE Communications Magazine*, vol. 59, no. 10, pp. 99–105, October 2021.
- [5] D. Wei, S. Zhang, S. Chen, H. Zhao and L. Zhu, “Research on anti-jamming technology of chaotic composite short range detection system based on underdetermined signal separation and spectral analysis,” *IEEE Access*, vol. 7, pp. 42298–42308, 2019.
- [6] Y. Hou, J. Webber, K. Yano, S. Kawasaki, S. Denno and Y. Suzuki, “Modeling and predictability analysis on channel spectrum status over heavy wireless LAN traffic environment,” *IEEE Access*, vol. 9, pp. 85795–85812, 2021.
- [7] S. Grimaldi, A. Mahmood and M. Gidlund, “Real-time interference identification via supervised learning: embedding coexistence awareness in IoT devices,” *IEEE Access*, vol. 7, pp. 835–850, 2019.
- [8] K. Nakanishi, H. Mori, T. Kumagaya and T. Aoki, “A novel signal detection method for interference from inverter microwave ovens in WLAN systems,” in Proc. 2017 IEEE Global Communications Conference (GLOBECOM 2017), pp. 1–6, 2017.
- [9] K. Nakanishi, H. Mori, T. Kumagaya and T. Aoki, “Signal detection method for interference from inverter microwave ovens in WLAN systems,” *IEEE Transactions on Cognitive Communications and Networking*, vol. 4, no. 2, pp. 368–378, June 2018.
- [10] M. Mehrnough and S. Roy, “Coexistence of WLAN network with radar: detection and interference mitigation,” *IEEE Transactions on Cognitive Communications and Networking*, vol. 3, no. 4, pp. 655–667, Dec. 2017.
- [11] J. Webber, K. Yano, N. Suga, Y. Hou, E. Nii, T. Higashimori, A. Mehdodniya, and Y. Suzuki, “WLAN interference identification using a convolutional neural network for factory environments,” *Journal of Communications*, vol. 16, no. 7, pp. 276–283, July 2021.
- [12] M. Di Renzo and S. Tretyakov, “Reconfigurable intelligent surfaces [Scanning the Issue],” *Proceedings of the IEEE*, vol. 110, no. 9, pp. 1159–1163, Sept. 2022.
- [13] B. Li, S. Wang, J. Zhang, X. Cao and C. Zhao, “Fast randomized-MUSIC for mm-Wave massive MIMO radars,” *IEEE Transactions on Vehicular Technology*, vol. 70, no. 2, pp. 1952–1956, Feb. 2021.
- [14] E. Björnson and L. Sanguinetti, “Power scaling laws and near-Field behaviors of massive MIMO and intelligent reflecting surfaces,” *IEEE Open Journal of the Communications Society*, vol. 1, pp. 1306–1324, 2020.
- [15] B. Li, S. Wang, J. Zhang, X. Cao and C. Zhao, “Fast randomized-MUSIC for mm-Wave massive MIMO radars,” *IEEE Transactions on Vehicular Technology*, vol. 70, no. 2, pp. 1952–1956, Feb. 2021.
- [16] Study on channel model for frequencies from 0.5 to 100 GHz, 3GPP TR 38.901 version 16.1.0 Release 16, Dec. 2019.

Yafei Hou received his Ph.D. degrees from Fudan University, China and Kochi University of Technology (KUT), Japan in 2007. He is Assistant Professor at the Graduate School of Natural Science and Technology, Okayama University, Japan. He is also a guest research scientist at Wave Engineering Laboratories, ATR Institute International, Japan from October 2016.

Kazuto Yano received the B.E. degree in electrical and electronic engineering, and the M.S. and Ph.D. degrees in communications and computer engineering from Kyoto University in 2000, 2002, and 2005, respectively. Currently, he

is Head of Dept. Wireless Communication Systems at Wave Engineering Laboratories, ATR Institute International, Japan.

Narisato Suga is assistant professor at Dept. of Information and Communications Engineering, Shibaura Institute of Technology, Tokyo, Japan and guest research scientist at Wave Engineering Laboratories, ATR Institute International, Japan.

Satoshi Denno received the M.E. and Ph.D degrees from Kyoto University, Kyoto, Japan in 1988 and 2000, respectively. He is a full professor at graduate school of natural science and technology, Okayama University, Japan.

Toshikazu Sakano received the M.E. and Ph.D degrees from Tohoku University, Sendai Japan in 1987 and 1998, respectively. He is Director at Wave Engineering Laboratories, ATR Institute International, Japan.