RIS-Aided Near-Field Localization and Channel Estimation for the Terahertz System

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Abstract—The affordable hardware cost of ultra-large (XL) reconfigurable intelligent surfaces (RIS) renders them attractive solutions for the performance enhancement of localization and communication systems. However, XL-RIS results in near-field propagation channels, especially for the high-frequency terahertz (THz) communication system, which poses significant challenges for localization and channel estimation. In this article, we focus on the spherical wavefront propagation in the near field of the THz system with the assistance of a RIS. A near-field channel estimation and localization (NF-JCEL) algorithm is proposed based on the derived second-order Fresnel approximation of the near-field channel model. To be specific, we carefully devise a down-sampled Toeplitz covariance matrix, which enables the decoupling and separate estimation of user equipment (UE) distances and angles of arrival (AoAs). Using the sub-space based method and one-dimensional search, we estimate the angles of arrival (AoAs) and user equipment (UE) distances. The channel attenuation coefficients are obtained through the least square (LS) method. To alleviate the impact of THz channel fading peaks caused by molecular absorption, estimates on multiple sub-bands are utilized for location estimation. Simulation results validate the superiority of the proposed NF-JCEL algorithm to the conventional far-field algorithm and show that higher resolution accuracy can be obtained by the proposed algorithm.

Index Terms—Near-field transmission, localization, intelligent reflecting surface (IRS), reconfigurable intelligent surface (RIS), terahertz (THz) communications.

I. INTRODUCTION

The sixth-generation (6G) mobile networks are expected to cater to various Internet of Things (IoT) applications such as healthcare, smart homes and intelligent manufacture [1]. These applications and services entail high-resolution location data from the involved collections of sensors, machines and other items. The terahertz band, typically between 100 gigahertz (GHz) and 10 terahertz (THz), has immense potentials to fulfill the requirements of 6G [2], such as its extensive spectrum resources [3], [4] and the capability of high-resolution positioning with subcentimeter-level accuracy [5], [6]. However, radio transmissions at high frequencies of THz band suffer from high path loss, and bad propagation conditions and are easy to be blocked. As its wavelength is on the order of 1 mm in THz communications, small objects in the path can affect the transmission, thus blocking the line-of-sight (LoS) path by humans or other static objects occurs frequently in many scenarios [7]. Consequently, mitigation techniques enabling THz communications via reflections in obstructed LoS path has become an important topic.

Recently, reconfigurable intelligent surfaces (RISs) have been regarded as a promising solution to overcome the blockage issue of the THz system. By carefully tuning the phase shifts of the reflecting elements, RIS can help constructively accumulate increased power at the target receiver and thus shows great potential to construct an intelligent radio environment. Thus, it was leveraged to help enhance the performance of the simultaneous wireless information and power transfer (SWIPT) system [8], [9] and multicell network [10]. Especially, in the localization system, it is shown that the RIS can help make the localization more accurate [11].

Conventionally, the user equipment (UE) localization problems aim to utilize the received signal strength (RSS), the time-difference-of-arrival (TDoA) [12], and the angle of arrival (AoA) of multiple sensors to distinguish the multiple signal directions from different emitters. The main idea is that all the geometric information for localization is included in the channel state information (CSI) measurements. Thus, the RIS-assisted localization accuracy is highly dependent on the necessity to acquire channel measurements [13]. However, the channels between the RIS and UEs, as well as the channel between the access point (AP) and the RIS, are cascaded [14]. In addition, the RIS has little signal processing capabilities, making channel estimation of RIS-assisted channels a challenging task [15]. Many researchers successfully managed to obtain the cascaded channel gains, such as [16], which have exploited the correlations between UEs to reduce the pilot overhead. In the RIS-assisted mmWave localization system, beam training was investigated in [17] to estimate AoAs and angles of departure (AoDs) of the LoS paths. In [18], the RSS was utilized in the RIS-aided localization system, and the RIS phase shifts were optimized to minimize the weighted probabilities of false localization. The achievable mean square error (MSE) of any
unbiased localization estimator is constrained by the localization performance limits. The Cramér-Rao lower bound (CRLB) is widely employed as a reliable metric benchmarks for practical estimators [19]. This is primarily due to the desire for unbiased estimation, and the preservation of estimation efficiency in non-linear transformations with sufficiently large data records [20]. It was shown in [21] that proper RIS phase shifts configuration can also help improve of the position/orientation estimation through position error bound (PEB) and rotation error bound (REB) analysis.

However, the above researches were mainly based on the assumption of far field channel model, where the planar wavefront was adopted. Thanks to the low hardware cost and reduced power consumption, a large number of passive and reflecting elements can be integrated into an RIS panel. In some envisioned industrial scenarios, the RIS panels can be installed to cover the entire roof and walls of a building. However, with the extra-large RIS panel, the typical indoor propagation distances of several meters are often not long enough to guarantee the validity of far-field conditions and of plane-wave assumptions. According to [22], to maintain a maximum phase difference of $\pi/8$ rad, the observation distance from the UE/AP to the RIS must be no less than the Fraunhofer distance $\frac{2L^2}{\lambda^2}$, where $L$ and $\lambda$ denote the maximal aperture of the RIS panel (i.e. the diagonal length of a rectangular panel) and radio wavelength, respectively. Thus, with a given RIS panel size, the short wavelength of terahertz makes the UEs very likely located in the near-field of the RIS panel. For instance, for an RIS panel with aperture 20 cm, the Fraunhofer distance is 13.3 m for the electrical magnetism (EM) waves at 50 GHz ($\lambda = 6$ mm), and it is increased to 93.3 m for the radio frequency increasing to 350 GHz ($\lambda = 0.86$ mm) in the THz band. Therefore, for the THz localization system, the impact of near-field impacts and the general spherical wavefront should be considered. With the spherical wavefront radio, the emitted EM wave will arrive at each reflecting element in the RIS array with different AoAs. This indicates that all array elements share a common AoA in the same path in the far-field model is no longer valid [23]. The near-field effect makes the channel modeling and CSI estimation for localization more challenging, and the near-field communications will profoundly degrade the localization performance [24], as also to be proved in this article.

The study on the RIS behavior in the near-field is just in its infancy. The RIS reflected power behavior was analyzed and measured in [25] under near/far-field conditions. The near-field channel modeling for active antenna arrays and RIS was investigated in [26]. In [27], a generic communication model with ultra-large (XL) array/surface was investigated with the consideration of the variations of signal phase, amplitude and aperture across array elements. The channel model mismatch was addressed in [28] by leveraging the misspecified Cramér-Rao lower bound (MCRB) to lower bound the localization error using a simplified mismatched model. A near-field codebook was developed in [29] for the XL RIS beam training by dividing the three-dimensional (3D) space into sampled points in the x-y-z coordinate system. The authors of [30] demonstrated that a RIS can serve as an anomalous mirror in the antenna array’s near field, by using antenna theory to calculate the electric field of a finite-size RIS. As for the radio localization approaches with RIS, there are only a few works with the consideration of spherical wavefront in the near-field. In [31], the Fisher information matrix (FIM) was analyzed for an uplink localization system using a RIS-based lens. The CRLB for RIS-assisted localization was investigated in [32] and the RIS phase shift was optimized to maximize the received signal to noise ratio (SNR). Similar researches were presented in [33], where FIM was analyzed for the RIS-assisted multipath localization system.

Most existing works such as [26], [27], [28] considered the near-field channel modeling and system performance analysis but did not address the issue of angle estimation and positioning algorithm in the near field. Although several RIS-assisted localization schemes have been proposed for the near-field scenario, including FIM/PEB/CRLB based estimation error analysis [31], [32], [33], [34], there is still a lack of specific positioning algorithms. In practice, RIS reflective elements are often organized in a rectangular manner, necessitating the consideration of a uniform planar array (UPA). However, current research on RIS localization, such as [35], [36], only focuses on the uniform linear array (ULA) of RIS. These approaches are not sufficient for the more general 3D localization system and cannot be directly applied to the RIS channel with a UPA as they only consider either the azimuth or elevation AoA/AoD. For RIS panels, the angles in both azimuth and elevation directions must be jointly estimated, which is not a simple extension of the linear case. Our work suggests that the down-sampled Toeplitz covariance matrix should be carefully re-examined, and angles in different directions should be decoupled to avoid two-dimensional grid searching. These tasks are not trivial for the UPA RIS system. Furthermore, the benefits of the adjustable phase shifts of the RIS panel are not fully exploited in current work. The RIS can be employed to efficiently increase the received signal samples from the same pilot data, thereby effectively improving the accuracy of the localization algorithm itself. Unfortunately, the integration of this approach into the near-field localization algorithm has not been adequately addressed in the current literature. Moreover, the existing localization approaches primarily focus on the single-user case, and these approach cannot be extended to scenarios where multiple users require positioning simultaneously. As a result, it remains unclear how to efficiently obtain the near-field locations of multiple UEs and the corresponding CSI parameters, such as the AoA/AoDs, in the THz localization system with RIS.

In this article, we investigate the localization and CSI estimation scheme in the near field of the THz system with the assistance of a RIS panel. Our contributions are summarized as follows:

- By considering the propagation of the spherical wavefront across the RIS UPA array, the near-field UE-RIS uplink channel is modeled. To reduce the complexity introduced by the different spatial paths at each reflecting element, the channel formulation based the second-order Taylor
approximation is derived, which involves both the UE distance and the AoAs.\(^1\)

- The impact of THz channel fading peaks are mitigated by using multiple sub-bands for angle/distance estimations. The RIS training phase shifts and pilots are designed to improve the rank deficiency of the RIS-assisted channel, so that the channel covariance of each sub-band can be obtained through least square (LS) method. Then, a down-sampled covariance matrix is derived for the UPA case so as to decouple the UE distances and the AoAs separately.
- Based on the down-sampled Toeplitz covariance matrix, the vertical and azimuth AoAs are estimated separately. Then, the UE distance can be estimated by the simple one-dimensional search, and the channel attenuation coefficients on multiple sub-bands are readily obtained by the LS method. Finally, the location is estimated by jointly considering the estimates on multiple sub-bands.
- Simulation results validate the effectiveness of the proposed near field joint channel estimation and localization (NF-JCEL) algorithm. Compared with the far-field algorithm, the proposed algorithm shows superiority in terms of localization and channel estimation inaccuracies.

The remainder of this article is organized as follows: Section II derives the near/far-field RIS-aided channel model and formulates the channel estimation problem. Section III develops the detailed algorithm for joint channel and localization estimation. In Section IV, the simulation results are presented to show the performance gain and the impact of system parameters, and Section V concludes the article.

Notation: For a vector \(x\), \(|x|\) and \((x)^T\) denotes its Euclidean norm and its transpose, respectively. For matrix \(A\), \(A^H\) and \(A^\dagger\) represent the conjugate transpose, the inverse and Moore-Penrose pseudoinverse operator, respectively. \(C^{M \times N}\) denotes the set of \(M \times N\) complex matrix. \(\text{diag}(x)\) represents the diagonal matrix \(X\) obtained from vector \(x\). \(a \otimes b\) represents the kronecker product of \(a\) and \(b\).

II. CHANNEL MODEL

Consider the uplink transmission of a THz localization system, as shown in Fig. 1. In the considered scenario, each UE is equipped with a single antenna, the AP is located in the XOZ plane, and the number of UEs is denoted as \(U\). It is assumed that the direct links between the AP and the UEs do not exist due to the blockage or unfavorable propagation environments. Note that when the LoS paths and the NLoS paths both exist, the orthogonal RIS profiles can be leveraged to differentiate LoS and NLoS paths as in [38], so that the proposed algorithm can still be applicable. Thus, an RIS is leveraged to construct the alternative AP-RIS-UE links for localization service.

The layouts of the AP antenna array and the RIS panel are shown in Fig. 2(a) and (b), respectively. The receive antenna array of the AP is assumed to be a ULA, and the number of AP’s antenna elements is denoted as \(N_A\). The distance between two antenna elements of the AP is denoted as \(\Delta_A\). As shown in Fig. 2(b), the RIS is installed on the wall at the YOZ-plane, and the RIS is equipped with \(N_R\) reflecting elements, where the number of the reflecting elements along the Y-axis and Z-axis are denoted as \((2 N_R^Y + 1)\) and \((2 N_R^Z + 1)\), respectively. Thus, \(N_R = (2 N_R^Y + 1) \times (2 N_R^Z + 1)\). The distance between two reflecting elements is denoted as \(\Delta_R\).

In the THz band, second-bounce or more reflections and scattering components are severely attenuated and thus they are negligible. Consequently, Similar to [32], [39], [40], we neglect the effects of reflections, scattering, and only consider the LoS path loss of the AP-IRS link and the IRS-UE links. Different from most of the existing works, we consider the channel model with the near-field effects.

At frequencies in the THz range, apart from path loss, the impact of molecular absorption cannot be overlooked. The phenomenon of molecular absorption exhibits peaks at specific carrier frequencies, resulting in spectrum windows with varying bandwidth, as depicted in Fig. 3. Thus, evaluating the complex

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\(^1\)The simplified approximation of near-field channel model is presented in conference version [37], but the following localization and channel estimation algorithm is only presented in this work.
channel coefficient $g_i^f (f_i, d_u)$ in the THz band requires consideration of several variables such as carrier frequency $f_i$, transmission distance $d_u$, and molecular absorption coefficient $K(f_i)$ [4]. The available bandwidths of low-absorption windows are distance-dependent and may vary among users. To tackle this, we partition the total THz bandwidth into sub-bands, with each sub-band exhibiting distinct channel losses. However, due to the variability of air composition, predetermining a user’s transmission sub-channel without distance information may lead to the risk of encountering channel fading peaks, as low-absorption windows are unreliable due to the variability of air composition. Therefore, to improve localization performance, we propose granting users access to multiple sub-bands simultaneously. In the following subsections, we illustrate the geometry relationships using the $i$-th sub-band.

### A. UE-RIS Link

In the LoS link, note that the waveband transmission of THz requires that phase shifts are related to the carrier frequency. Let $f_i$ denote the central frequency of the $i$-th sub-band, and $\lambda_i = \frac{c}{f_i}$ is the wavelength. Thus, with the spherical wavefront, the frequency-dependent receiving array response $a_{RISIS}^i$ for UE $u$ at the RIS’s $m$-th element is given by

$$ a_{RISIS}^i[m] = \exp \left( -\frac{2\pi}{\lambda_i} (d_{RISIS}^m - d_u^0) \right), \quad (1) $$

where $d_{RISIS}^m$ represents the distance from the RIS’s $m$-th element to UE $u$, and $d_u^0$ represents the distance from the central reflecting element to UE $u$. Then, the complex channel gain of UE $u$-RIS link of the $i$-th sub-band is denoted as

$$ h_{RISIS}^i = g_R^i a_{RISIS}^i, \quad (2) $$

where $g_R^i$ represents the complex channel attenuation coefficient. It should be noted that accurately modeling the the channel fading $g_R^i$ is not practical, resulting from the fact that molecular absorption coefficient is associated with the atmospheric pressure, relative humidity, and temperature of the transmission medium [41]. Therefore, this work assumes the complex channel coefficient to be unknown, and the cascaded channel gain will be estimated in the following sections.

Denote the center of the RIS panel as the phase reference point, and its coordinate is $(x_R, y_R, z_R)$. Suppose that the $m$-th reflecting element is located at $(x_R, y_R + m_y \Delta R, z_R + m_z \Delta R)$, where $m_y = -N^Y, \ldots, 0, \ldots, N^Y$, and $m_z = -N^Z, \ldots, 0, \ldots, N^Z$. The index $m$ of the reflecting element can be expressed as

$$ m = m_z (2N^Y + 1) + m_y, m \in [-N_0, \ldots, N_0], \quad (3) $$

where $N_0 = \frac{N^Y - 1}{2} = N^Y (2N^Y + 1) + N^Y$.

As shown in Fig. 4, the projection of distance $d_{RISIS}^m$ on the XOY plane is denoted as $d_{RISIS}^{0,m}$, given by

$$ d_{RISIS}^{0,m} = \sqrt{(m_y \Delta R)^2 + (m_0^{0,m})^2 - 2 \sin \theta_{u,0} m_y \Delta R}, \quad (4) $$

where $d_{RISIS}^{0,m}$ denotes the projection of distance $d_u^0$ on the XOY plane, given by

$$ d_{RISIS}^{0,m} = d_u^0 \cos \phi_{u,0}. \quad (5) $$

Then, the distance $d_{RISIS}^m$ is calculated as

$$ d_{RISIS}^m = \sqrt{(d_u^0 \sin \phi_{u,0} + m_z \Delta R)^2 + (l_{RISIS}^m)^2}. \quad (6) $$

Substituting (4) and (5) into (6), one obtains

$$ d_{RISIS}^m = ((m_0 \Delta R)^2 + (m_z \Delta R)^2 + (d_u^0)^2 - 2d_u^0 m_y \Delta R \cos \phi_{u,0} \sin \theta_{u,0} + 2m_z \Delta R d_u^0 \sin \phi_{u,0})^{1/2}. \quad (7) $$

Letting $y = \frac{m_y \Delta R}{d_u^0}$, and $z = \frac{m_z \Delta R}{d_u^0}$, the distance between the $m$-th reflecting element and UE $u$ can be represented as

$$ d_{RISIS}^m = d_u^0 (y^2 + z^2 + 1 - 2y \cos \phi_{u,0} \sin \theta_{u,0} + 2z \sin \phi_{u,0})^{1/2} \equiv d_u^0 F(y, z). \quad (8) $$

In order to compute the distance $d_{RISIS}^m$ in (8), we consider the following simplifications. First of all, for ease of exposition, the first and second order derivatives of $F(y, z)$ with respect to $y$ and/or $z$ are given by

$$ \frac{\partial F}{\partial y} = y - \cos \phi_{u,0} \sin \theta_{u,0}, \quad \frac{\partial F}{\partial z} = z + \sin \phi_{u,0}, \quad (9) $$

$$ \frac{\partial^2 F}{\partial y^2} = 1 + 2z + 2z \sin \theta_{u,0} - (\cos \phi_{u,0} \sin \theta_{u,0})^2, \quad (10) $$

$$ \frac{\partial^2 F}{\partial z^2} = 1 + y^2 - 2y \cos \phi_{u,0} \sin \theta_{u,0} - (\sin \phi_{u,0})^2, \quad (11) $$

$$ \frac{\partial^2 F}{\partial z \partial y} = -2y - 2 \cos \phi_{u,0} \sin \theta_{u,0} (z + \sin \phi_{u,0}) \quad (12) $$

1) Far Field Approximation: From [22], the far field of the RIS can be defined as the set of observation distances $R$ that are greater than the Fraunhofer distance $R_f$, i.e.,

$$ R \geq R_f = \frac{2L^2}{\lambda_i}. \quad (13) $$
This definition corresponds to the maximum phase difference, \( \pi/8 \), of radio waves between any two reflecting elements. In this article, we select the center of the RIS panel as the reference point, as shown in (1), thus the aperture of the RIS UPA should be the distance from panel vertex to the panel center as

\[
L = \sqrt{(M_y \Delta R)^2 + (M_z \Delta R)^2}. \tag{14}
\]

As a result, when UE \( u \) is located in the far field of the RIS panel, i.e.,

\[
d_{R,u}^m > \frac{L^2}{\lambda_i} = 2 \left( \frac{(M_y \Delta R)^2 + (M_z \Delta R)^2}{\lambda_i} \right),
\]

where \( d_{R,u}^m \) denotes the distance of UE \( u \) to the nearest RIS panel vertex. Then, (7) can be approximated by the first-order Taylor expansion as

\[
d_{R,u}^m \approx d_{R,u}^0 (F(y,z)|_{y=0,z=0} + \frac{\partial F}{\partial y}|_{y=0} y + \frac{\partial F}{\partial z}|_{z=0} z) = d_{R,u}^0 (1 - \cos \phi_{u,0} \sin \theta_{u,0} y + \sin \phi_{u,0} z)
\]

\[
= d_{R,u}^0 \left( \frac{m_z \Delta R}{d_{R,u}^0} \sin \phi_{u,0} - \frac{m_y \Delta R}{d_{R,u}^0} \sin \theta_{u,0} \cos \phi_{u,0} + 1 \right) = m_z \Delta R \sin \phi_{u,0} - m_y \Delta R \sin \theta_{u,0} \cos \phi_{u,0} + d_{R,u}^0. \tag{15}
\]

Therefore, in this case, the array response is characterized only by the azimuth and vertical AoAs. For ease of expression, we use \( \omega_u = \sin \phi_{u,0} \) and \( \varphi_u = \sin \theta_{u,0} \cos \phi_{u,0} \) to denote the AoAs. Then, the array response for the far field can be denoted as

\[
a_{R,u}^{\psi} (\omega_u, \varphi_u)[m] = \exp \left( -\frac{2\pi}{\lambda_i} J_m (\omega_u, \varphi_u) \right). \tag{16}
\]

where

\[
J_m (\omega_u, \varphi_u) = m_z \Delta R \omega_u - m_y \Delta R \varphi_u. \tag{17}
\]

The relationship between \( m \) and \( (m_y, m_z) \) is given by (3).

According to (13), the Fraunhofer distance would be very large if an extra-large RIS is utilized. When the RIS is working at THz spectrum, it is very likely that some UEs are in the near field when the RIS is deployed for indoor applications such as localization. In this case, the spherical wavefront of the EM waves should be considered.

2) Near Field Formulation: When UE \( u \) is located at the near field of the RIS panel, i.e., the Fresnel region \( d_{R,u}^m \in [0.62 \frac{L^2}{\lambda_i}, 2 \frac{L^2}{\lambda_i}] \), a good approximation is based on the Fresnel approximation, which corresponds to the second-order Taylor expansion [42]. So far, the second-order Fresnel approximation results have been developed for the array with ULA geometry [42], [43], [44], but they cannot be directly applied to the two-dimensional RIS UPA case. Thus, we derive the two-dimensional Fresnel approximation as

\[
F(y, z) \approx F(y, z)|_{y=0, z=0} + \frac{\partial F}{\partial y}|_{y=0} y + \frac{\partial F}{\partial z}|_{z=0} z + \frac{1}{2} [y, z] \times \Delta^2 F \times [y, z]^T, \tag{18}
\]

where

\[
\Delta^2 F = \begin{bmatrix} \frac{\partial^2 F}{\partial y^2}|_{y=0, z=0} & \frac{\partial^2 F}{\partial y \partial z}|_{y=0, z=0} \\ \frac{\partial^2 F}{\partial z \partial y}|_{y=0, z=0} & \frac{\partial^2 F}{\partial z^2}|_{y=0, z=0} \end{bmatrix} = \begin{bmatrix} 1 - (\cos \phi_{u,0} \sin \theta_{u,0})^2 & \cos \phi_{u,0} \sin \theta_{u,0} \sin \phi_{u,0} \\ \cos \phi_{u,0} \sin \theta_{u,0} \sin \phi_{u,0} & 1 - (\sin \phi_{u,0})^2 \end{bmatrix}.
\]

Then, (18) can be reformulated as

\[
F(y, z) \approx 1 + \omega_u y - \varphi_u z + \frac{1}{2} (\varphi_u y^2 + \omega_u z^2 + 2 \varphi_u \omega_u y z), \tag{19}
\]

where \( \varphi_u = 1 - \omega_u^2 \) and \( \varphi_u = 1 - \varphi_u^2 \). Then, the distance of the \( m \)-th reflecting element \( d_{R,u}^m \) can be approximated as

\[
d_{R,u}^m \approx m_z \Delta R \omega_u - m_y \Delta R \varphi_u + \frac{1}{2} \varphi_u \cos \phi_{u,0} \sin \theta_{u,0} y + \sin \phi_{u,0} z
\]

\[
= m_z \Delta R \omega_u - m_y \Delta R \varphi_u - \frac{(m_z \Delta R \omega_u - m_y \Delta R \varphi_u)^2}{2 \varphi_u^0}
\]

\[
\approx J_m (\omega_u, \varphi_u) + Q_m (\omega_u, \varphi_u, d_{R,u}^0) + d_{R,u}^0, \tag{20}
\]

where

\[
Q_m (\omega_u, \varphi_u, d_{R,u}^0) = \frac{1}{2 \varphi_u^0} \left( (m_z \Delta R)^2 + (m_y \Delta R)^2 \right)
\]

\[
- \frac{1}{2 \varphi_u^0} \left( m_z \Delta R \omega_u - m_y \Delta R \varphi_u \right)^2 \tag{21}
\]

In the near-field case, apart from the azimuth and vertical angles, the array response is also dependent on \( d_{R,u}^0 \), which is the distance from UE \( u \) to the center of RIS. Then, the near-field array response can be approximated as

\[
a_{R,u}^{\psi} (\omega_u, \varphi_u, d_{R,u}^0)[m] = \exp \left( -\frac{2\pi}{\lambda_i} J_m (\omega_u, \varphi_u) + Q_m (\omega_u, \varphi_u, d_{R,u}^0) \right). \tag{22}
\]

It can be verified that \( a_{R,u}^{\psi} (\omega_u, \varphi_u, d_{R,u}^0)[m] \to a_{R,u}^{\psi} (\omega_u, \varphi_u)[m] \) when \( d_{R,u}^0 \) is sufficiently large. In other words, the near field case reduces to the far-field case. Then, in the near field, the complex channel gain from UE \( u \) to the RIS is denoted as

\[
h_{u,R}^i = \frac{g_{R,u}}{d_{R,u}^0} \frac{a_{R,u}^{\psi} (\omega_u, \varphi_u, d_{R,u}^0)}{d_{R,u}^0}, \tag{23}
\]

where the \( m \)-th element of \( a_{R,u}^{\psi} (\omega_u, \varphi_u, d_{R,u}^0) \) is given by (22).

Overall, the distance \( d_{R,u}^m \) can be approximated by the near-field model (20) and the far-field model (15), and the approximation errors are shown in Fig. 5 with labels “NF” and “FF”, respectively. In Fig. 5, the Y-axis denotes the summation of approximation errors of \( d_{R,u}^m \) for all \( m = N_y^R, N_y^R + 1, \ldots, N_y^R, \ldots, N_y^R + 1 + N_y^R \). As expected, it is observed that the proposed near-field model is more accurate than the far field model, as the approximation errors of “NF” are much less than that of “FF”. Also, when the distance between UE
and the RIS panel increases, the approximation error of the near-field model also decreases, which indicates that the “NF” model becomes more accurate for longer transmission distance. Also, the array response given in (1) can be approximated by the near-field steering vector (22) and the far-field steering vector (16), respectively, i.e., \( a_R \approx a^F_R \) and \( a_R \approx a^E_R \).

### B. RIS-AP Link

It is assumed that the LoS channel between the RIS and the AP is varying slowly. Due to the spherical nature of the wavefront, the transmission distances from each element of the RIS to each antenna element of the AP array determine the phases of the received signals at the AP. According to [45], [46], [47], a high-rank channel model of the RIS-AP link can be obtained with a proper deployment. With the spherical wave modeling, the normalized channel gain of the RIS-AP link is denoted as \( G_{A,R,i} \), which collects the channel elements of the RIS-AP LoS link. The \((m,n)\)-th element of the \( G_{A,R} \) is given by [45]

\[
G_{A,R}(m,n) = \exp \left( \frac{2\pi}{\lambda} r_{m,n} \right),
\]

where \( r_{m,n} \) denotes the path length between the \( m\)th antenna element of the AP and the \( n\)th reflecting element. Letting \( g_A \) denote the common large-scale path loss attenuation, the complex channel gain is then given by [46]

\[
H_{A,R}^i = g_A G_{A,R}^i.
\]

### C. Cascaded Channel

Let \( E_{RIS} = \text{diag}(e) \in \mathbb{C}^{N_R \times 1} \) denote the phase shift matrix of the RIS, where \( e \) denotes the phase shift vector of the RIS. Overall, the cascaded channel of UE \( u \) on sub-band \( i \) is

\[
H_u^i = g_{u,i} g_{R,u}^i E_{RIS} a_{u,i},
\]

where \( g_{u,i} = g_A g_{R,u}^i \) and \( a_{u,i} = a_{R,u}^i (\omega_u, \varphi_u, \theta_u) \).

### III. JOINT CHANNEL AND LOCALIZATION ESTIMATION

Suppose that UEs utilize the same pilot sequence on all sub-bands. In \( t \)-th pilot duration, the transmit signal of the \( U \) UEs is denoted as \( x_u = [x_1(t), \ldots, x_U(t)]^T \in \mathbb{C}^{U \times 1} \). The received signal at the AP on sub-band \( i \) is

\[
y_i(t) = G_{A,R}^i E_{RIS}(t) \sum_{u=1}^{U} g_{u,i}^t a_{u,i} x_u(t) + n_i(t)
\]

where \( A_i = [g_{1,i}, \ldots, g_{U,i}] \), and \( n_i(t) \) denotes the Gaussian noise vector with the distribution of \( \mathcal{CN}(0, \sigma^2 I) \).

In the AP-RIS link, as the locations of the RIS and the AP are known as prior, the distances \( r_{m,n} \) between the elements of the AP and that of the RIS can be readily obtained. To locate UE \( u \), the unknown parameters that need to be estimated are:

- \( \omega_u, \varphi_u \) and \( d_0^u \), which depends on the location of UE \( u \) in the RIS-UE \( u \) link;
- \( g_{u,i} \), which is the cascaded channel attenuation coefficient and vary at different THz sub-bands.

Note that the unknown angle and distance information is involved in the \( A_i \) in each sub-band. However, due to the fact that the steering vector are frequency-dependent, we process the angel estimation by each sub-band to avoid the impacts of beam squint effects on the localization degradation. Thus, in the following Section III.A–III.C, the processing procedure is conducted on a single sub-band \( i \). For simplicity, the subscript \( i \) of the denotations is omitted.

### A. RIS Training Phase Shifts and Pilot Design

To obtain the unknown channel matrix \( A \) on a sub-band, the simplest method is to adopt the LS method. However, in the considered scenario, the number of antenna elements of the AP is less than that of the RIS panel, i.e., \( N_A < N_R \), resulting in that the LS estimation cannot be directly applied. Therefore, to obtain the unique estimation of \( A \), we utilize different RIS phase shift vectors \( e(t) \) and pilot data \( x_i \).

Fig. 6 shows the proposed design of RIS training phase shift vectors and pilot data on each sub-band. The pseudo-random (PN) pilot sequences are utilized as the transmit pilot at different time slots, for instance, the PN sequences. The transmit signal from UE \( u \) is denoted as \( x_u \) with the normalization constraint that \( E[|x_u|^2] = P_u \), which denotes the transmit power of UE \( u \) on each sub-band. To keep orthogonality between different users, the pilot sequences from different users are statistically orthogonal with \( E[x_u x_k^\dagger] = 0 \), for all \( k \neq u \).

As shown in Fig. 6, the RIS phase shift vector changes for \( S \) times in a pilot data duration, and the set of phase shift vectors is denoted as \( \{e_1, \ldots, e_S\} \). The number of RIS training phase shift vectors is denoted as \( S \), and the required number of pilot data is denoted as \( \tau \). Let \( y_i \) denote the composited signal for the \( t \)-th pilot data duration, which collects the received signal with
different phase shift vectors as
\[ y_t = G_{RIS}A x_t + n_t, \]  
(28)
where the received vector \( y_t \) has the size of \( N_A S \times 1 \), \( y_t = [y(t_1)^T, \ldots, y(t_S)^T]^T \), and \( n_t = [n(t_1)^T, \ldots, n(t_S)^T]^T \). The matrix \( G_{RIS} \) with size \( S N_A \times N_R \) collects the channel gains incurred by \( S \) different phase shift vectors, which are
\[
G_{RIS} = [(G_{AR,\text{diag}}(e_1))^T, G_{AR,\text{diag}}(e_2)^T, \ldots, G_{AR,\text{diag}}(e_S)^T]^T.
\]
Then, we have the LS estimation for \( Ax_t \) as
\[
\hat{A} x_t = (G_{RIS}^H G_{RIS})^{-1} G_{RIS}^H y_t = H_{RIS} y_t.
\]
(29)
Let \( H_{RIS}^H \) denote the Moore-Penrose pseudoinverse of \( G_{RIS} \). Consequently, the array covariance matrix can be estimated as
\[
\hat{R} = \mathbb{E}[H_{RIS}^H y_t y_t^H (H_{RIS})^H] = AA^H + \sigma^2 (G_{RIS}^H G_{RIS})^{-1}.
\]
(30)
**Remark 1:** Note that the rank of the cascaded channel \( G_{RIS} \) can be increased by employing diverse phase shifts of RIS. Insufficient training phases may lead to the presence of numerous small eigenvalues in the matrix \( G_{RIS} \), resulting in amplified output noise when employing the LS estimator. Specifically, the matrix inversion operation \( (G_{RIS}^H G_{RIS})^{-1} \) is prone to such noise amplification. In addition, considering the computational complexity of implementing high-order matrix inversions in practical systems, we employ an approximate calculation method, denoted as \( \hat{G}_{\text{inv}} \), to estimate \( (G_{RIS}^H G_{RIS})^{-1} \). To obtain \( \hat{G}_{\text{inv}}^H \), we perform eigenvalue decomposition on the matrix \( G_{RIS}^H G_{RIS} \) and extract its \( k \) largest eigenvalues that surpass a predetermined threshold value \( \delta_H \), along with their corresponding eigenvectors. By utilizing these principal eigenvalues and eigenvectors, the approximate \( \hat{G}_{\text{inv}}^H \) can then be obtained. In practice, the threshold value \( \delta_H \) set to \( 10^{-8} \) effectively preserves high approximation accuracy while mitigating significantly smaller eigenvalues.

By collecting the received signal \( y_t \) with different \( \tau \) pilot durations, the estimated array covariance matrix \( \hat{R} \) of \( R \) is given by
\[
\hat{R} = \frac{1}{\tau} \sum_{t=1}^\tau \hat{A} x_t (\hat{A} x_t)^H,
\]
(31)
where the total number of snapshots is \( \tau \).

**Remark 2:** To ensure precise localization of users, the appropriate pattern of training phase shifts of RIS is of paramount importance. The phase-adjustable property of the RIS enables it to align with the AoAs of UE, thereby enhancing the received energy from the UEs. Considering that the locations of UE are unknown, we propose leveraging existing RIS phase designs, such as the Discrete Fourier Transform (DFT) matrix and random phase schemes. Specifically, random phase schemes exhibit a higher probability of aligning with the UEs compared to the DFT scheme, which partitions the interval of \( 2\pi \) into \( N_R \) segments. The impact of different patterns of RIS training phase is illustrated in Section IV.C with more details.

**B. Estimation of AoAs**

Without noise, we have the following explicit expression
\[
R = AA^H = \sum_{u=1}^U |a_u|^2 a_u a_u^H.
\]
(32)
Then, the \((p,q)\)-th element of covariance \( R \) is given by
\[
R(p,q) = \sum_{u=1}^U |a_u|^2 \exp\left(-j \frac{2\pi}{\lambda} (J_{p,q} + Q_{p,q})\right),
\]
(33)
where \( J_{p,q} = J_p(\omega_u, \varphi_u) - J_q(\omega_u, \varphi_u) \), \( Q_{p,q} = Q_p(\omega_u, \varphi_u, \Delta\varphi_u) - Q_q(\omega_u, \varphi_u, \Delta\varphi_u) \). Furthermore, according to the definitions of \( J_p(\omega_u, \varphi_u) \) and \( Q_p(\omega_u, \varphi_u, \Delta\varphi_u) \) given beneath (17) and (21), we have the differences formulated as
\[ Q_{p,q} = \frac{1}{2d_u^2} (\Delta^2 (p_z^2 + p_y^2)) + \frac{1}{2d_u^2} (q_z \Delta_R \omega_u - q_y \Delta_R \varphi_u)^2,
\]
where \( J_{p,q} = (p_z - q_z) \Delta_R \omega - (p_y - q_y) \Delta_R \varphi_u \).

The indices of \( J_p \) and \( Q_p \) is denoted as \( p(z,p_y) \). Similarly, we denote the indices of \( J_q \) and \( Q_q \) as \( q(z,p_y) \).\( p_y, q_y, p_z, q_z \) are indexes along Y-axis and Z-axis, and\( p_y, q_y = -N_Y, \ldots, N_Y, p_z = -N_Z, \ldots, N_Z \).

According to (3), we have
\[
p(p_z,p_y) = N_Y^2 (2N_Y + 1) + N_Y^2 + p_z(2N_Y + 1) + p_y,
\]
and\( q(z,p_y) = N_Y^2 (2N_Y + 1) + N_Y + q_z(2N_Y + 1) + q_y \).

Then, it is found that for all \( p_y = -q_y \) and \( p_z = -q_z \), one obtains
\[
J_{p,q} = 2p_z \Delta_R \omega - 2p_y \Delta_R \varphi_u, \quad Q_{p,q} = 0.
\]
In other words, the quadratic term is eliminated for the element of \( R(p(p_z,p_y), q(z,p_y)) \) in the covariance matrix \( R \), which are
\[
R(p(p_z,p_y), q(z,p_y)) = \sum_{u=1}^U |a_u|^2 \exp\left(-j \frac{2\pi}{\lambda} (2J_p(\omega_u, \varphi_u))\right).
\]

Based on the above observation, we provide the following approach to separate the distance and the AoAs in the covariance matrix. First, we define steering vectors as
\[
v_u(\omega_u)[z] = \exp\left(-j \frac{2\pi}{\lambda} (z \Delta_R \omega_u)\right), \quad z = 0, \ldots, N_Z,
\]
\[
s_u(\varphi_u)[y] = \exp\left(-j \frac{2\pi}{\lambda} (y \Delta_R \varphi_u)\right), \quad y = 0, \ldots, N_Y,
\]
\[
b_u(\omega_u, \varphi_u) = v_u(\omega_u) \otimes s_u(\varphi_u)
\]
\[= [v_u(\omega_u)[0] s_u(\varphi_u)[0], \ldots, v_u(\omega_u)[N_Z] s_u(\varphi_u)[0]]^T.
\]
Then, we define the correlation matrix \( R_b \) as
\[
R_b = \sum_{u=1}^U |a_u|^2 b_u(\omega_u, \varphi_u) b_u^H(\omega_u, \varphi_u),
\]
(34)
Defining the following function
\[ e(z, y) = \sum_{u=1}^{U} |g_u|^2 \exp \left( -\frac{4\pi}{\lambda} (z \Delta_R \omega_u - y \Delta_R \varphi_u) \right), \] (35)
we can represent the covariance matrix \( \mathbf{R}_b \) as (36) shown at the bottom of the this page. Note that
\[ \mathbf{R}(p(z, y), q(-z, -y)) = e(z, y) = (e(-z, -y))^T. \]

For instance, the first element of the matrix \( \mathbf{R}_b \), i.e., \( e(0, 0) \) is the same as \( \mathbf{R}(p(0, 0), q(0, 0)) \), where
\[ p(0, 0) = N_R^Z (2 N_R^Y + 1) + N_Y = \frac{N_R - 1}{2}, \]
\[ q(0, 0) = N_R^Z (2 N_R^Y + 1) + N_Y = \frac{N_R - 1}{2}. \]

Let \( N_b \) represent the length of vector \( \mathbf{b}_u \), and
\[ N_b = (N_R^Z + 1) \times (N_R^Y + 1). \]

The index of the center reflecting element is denoted as
\[ N_0 = \frac{N_R - 1}{2}. \]
Then, the index functions can be represented as
\[ p(z, y) = N_0 + z(2 N_R^Y + 1) + y \]
\[ q(-z, -y) = N_0 - z(2 N_R^Y + 1) - y. \]

Letting \( N_i = N_0 + i(2 N_R^Y + 1) \) and \( \overline{N}_i = N_0 - i(2 N_R^Y + 1) \), the element matrix \( \mathbf{S}_i \) with size \((N_R^Y + 1) \times (N_R^Y + 1)\) is given by (37) shown at the bottom of this page.

Utilizing \( \mathbf{S}_i \), we construct the down-sampled Toeplitz matrix with size \(N_b \times N_b\) as
\[ \mathbf{T} = \begin{bmatrix} \mathbf{S}_0 & \mathbf{S}_{-1} & \cdots & \mathbf{S}_{-N_R^Z} \\ \mathbf{S}_1 & \mathbf{S}_0 & \cdots & \mathbf{S}_{-N_R^Z + 1} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{S}_{N_R^Z} & \mathbf{S}_{N_R^Z-1} & \cdots & \mathbf{S}_0 \end{bmatrix}. \] (38)

We can derive that
\[ \mathbf{T} = \sum_{u=1}^{U} |g_u|^2 \mathbf{b}_u(\omega_u, \varphi_u) \mathbf{b}_u^H(\omega_u, \varphi_u). \] (39)

It is observed that the sampled correlation matrix \( \mathbf{T} \) only depends on the azimuth and vertical angles, and which is the same as the far-field case.

Remark 3: By leveraging (38), the distance and the AoAs can be decoupled by the sampled correlation matrix \( \mathbf{T} \). Then, the conventional far-field angle estimation approaches can be leveraged in this case, such as the two-dimensional MUSIC-like spectrum peak searching [48]. Note that the sampled steering vectors \( \mathbf{u}_1(\omega_u) \) and \( \mathbf{s}_u(\varphi_u) \) have twice the spacing of the original RIS element separations. As a result, a constraint needs to be imposed that the separation of the RIS elements should not exceed \( \frac{1}{2} \) to ensure unique estimation of AoAs. However, note that the MUSIC algorithm requires eigendecomposition. Note that there are approaches such as information theoretic criteria [49], [50] and K-means clustering algorithm [51] that can be used for estimating the number of UEs. Thus, in the following, we propose a computationally efficient subspace-based method for the AoA estimation.

First, we define matrix \( \mathbf{B} = [g_0 \mathbf{b}_1, \ldots, g_U \mathbf{b}_U] \), and divide the \( N_b \times U \) matrix into two parts as
\[ \mathbf{B} \triangleq \begin{bmatrix} \mathbf{B}_1 & \mathbf{B}_2 \end{bmatrix}, \] (40)
where matrix \( \mathbf{B}_1 \) contains the first \( U \) rows of \( \mathbf{B} \) and \( \mathbf{B}_2 \) contains the remaining \( N_b - U \) rows. Note that \( \mathbf{B}_1 \) is a Vandermonde matrix. Assuming that the \( U \) UEs are from distinct directions, \( \mathbf{B}_1 \) has the full rank of \( U \), and the rows of \( \mathbf{B}_2 \) can be expressed as a linear combination of linearly independent rows of \( \mathbf{B}_1 \) [52], [53]. Equivalently, there is a \( U \times (N_b - U) \) linear operator \( \mathbf{P}_1 \) between \( \mathbf{B}_1 \) and \( \mathbf{B}_2 \) as
\[ \mathbf{P}^H \mathbf{B}_1 = \mathbf{B}_2, \] (41)
and the linear operator \( \mathbf{P}_1 \) can be calculated as
\[ \mathbf{P}_1 = (\mathbf{B}^H \mathbf{B})^{-1} \mathbf{B}^H. \] (42)

Then, we utilize the correlation matrix to obtained linear operator \( \mathbf{P}_1 \). The correlation matrix \( \mathbf{T} \) can be represented as
\[ \mathbf{T} = \mathbf{B} \mathbf{B}^H = \begin{bmatrix} \mathbf{B}_1 \mathbf{B}_1^H \\ \mathbf{B}_2 \mathbf{B}_2^H \end{bmatrix} = \begin{bmatrix} \mathbf{T}_1 \in \mathbb{C}^{U \times N_R} \\ \mathbf{T}_2 \in \mathbb{C}^{(N_b-U) \times N_R} \end{bmatrix} \] (43)
where \( \mathbf{T}_1 \) consists of the first \( U \) rows and \( \mathbf{T}_2 \) consists of the remaining \( (N_b - U) \) rows. Then, the relationship between the
submatrices of $T_1$ and $T_2$ is

$$P_1^H T_1 = T_2.$$  \hfill (44)

Then, the linear operator $P_1$ can be found from $T_1$ and $T_2$ as

$$P_1 = (T_1^H T_1)^{-1} T_1^H T_2.$$  \hfill (45)

With the obtained linear operator $P_1$, we have

$$Q^H B = 0_{N_u \times U},$$  \hfill (46)

where $Q^H = [P_1^H, -I_{N_u - U}]$. As a result, the columns of $Q$ are in the null space of $B$, i.e., $N(B)$ and the orthogonal projector onto this subspace $N(B)$ is given by

$$\Pi_Q = Q (Q^H Q)^{-1} Q^H.$$  \hfill (47)

Then, we can infer that $\Pi_Q z_u = 0$, $\forall u = 1, \ldots, U$. Define

$$v(\omega)[z] = \exp \left( -j \frac{2\pi}{\lambda} (z_1 \Delta_R \omega) \right), z = 0, \ldots, N_R,$$

$$s(\varphi)[y] = \exp \left( -j \frac{2\pi}{\lambda} (-2y \Delta_R \varphi) \right), y = 0, \ldots, N_R.$$  \hfill (48)

Then, the angles can be estimated in a manner similar to the MUSIC method by minimizing the following cost function as

$$f(\omega, \varphi) = (v(\omega) \otimes s(\varphi))^H \Pi_Q (v(\omega) \otimes s(\varphi)),$$  \hfill (49a)

s.t. $e^H s(\varphi) = 1,$  \hfill (49b)

where $e = [1, 0, \ldots, 0]^T$, and the constraint (49b) is introduced to avoid the trivial solution $s(\varphi) = 0$. Then, the objective function is reformulated as

$$f(\omega, \varphi) = (v(\omega)^H \otimes I_{N_R}^+) \Pi_Q (v(\omega) \otimes 1_{N_R}) s(\varphi)$$

$$= s(\varphi)^H \Theta(\omega) s(\varphi),$$  \hfill (50)

where $\Theta(\omega) = [v(\omega)^H \otimes I_{N_R}^+] \Pi_Q [v(\omega) \otimes 1_{N_R}]$.

We construct the following Lagrange function

$$\mathcal{L} = s(\varphi)^H \Theta(\omega) s(\varphi) - \epsilon (e^H s(\varphi) - 1),$$  \hfill (51)

where $\epsilon$ is the introduced Lagrange multiplier. Then, one obtains

$$\frac{\partial \mathcal{L}}{\partial s(\varphi)} = 2 \Theta(\omega) s(\varphi) - \epsilon e.$$

We can infer that $s(\varphi) = \zeta \Theta^{-1}(\omega)e$, where $\zeta$ is a non-zero constant. As $e^H s(\varphi) = 1$, we have $\zeta = (e^H \Theta^{-1}(\omega)e)^{-1}$. Then, one obtains

$$s(\varphi) = \frac{\Theta^{-1}(\omega)e}{e^H \Theta^{-1}(\omega)e}.\hfill (53)$$

Then, substituting (53) into the objective function (50), Problem (49) is transformed into

$$\min_{\omega} f(\omega) = \frac{1}{e^H \Theta^{-1}(\omega)e}.$$  \hfill (54)

Then, the optimal solution to (54) is

$$\omega^* = \arg \max e^H \Theta^{-1}(\omega)e.$$  \hfill (55)

**Remark 4:** In practice, two-layer grids can be used for searching the optimal solution $\omega^*$. To be specific, the grid with large step-size is used for the preliminary coarse search. Then, based on the preliminary coarse results, the finer grid is then applied to obtain the fine results. Furthermore, due to the presence of noise, the energy peak will leakage to adjacent grid points. Therefore, to enhance the position accuracy, it is suggested to take several largest values as estimation candidates, and then use the clustering method, such as the K-mean method [54], to obtain a more accurate estimation.

Recall that $\omega_1 = \sin \phi_1$ and $\varphi_u = \sin \theta_u \cos \phi_u$, where $\phi_u$ and $\theta_u$ represent the vertical and azimuth AoAs of UE $u$, respectively. Then, we can search the interval $\omega_u \in [-1, 1]$, and obtain $U$ largest peaks of the (1,1)-th element of $\Theta^{-1}(\omega)$. These peaks correspond to the vertical AoAs of UEs, denoted as $[\omega_1, \omega_2, \ldots, \omega_U]$. Then, for the composite angle $\varphi_u$, according to (53), we can obtain the $U$ vectors $[\tilde{s}(\varphi_1), \tilde{s}(\varphi_2), \ldots, \tilde{s}(\varphi_U)]$. Let $|x|$ denote the phase angles (in radians) of the elements of $x$.

$$\tilde{q}_u = \langle \tilde{s}(\varphi_u) = [0, \frac{4\pi}{\lambda} \Delta_R \varphi_u, \ldots, \frac{4\pi}{\lambda} \Delta_R^{N_R} \varphi_u]^T, \hfill (56)$$

and vector $p = [0, \frac{2\pi}{\lambda} \Delta_R, \ldots, \frac{2\pi}{\lambda} \Delta_R^{N_R}]^T$. Then, we utilize the LS estimator to obtain the estimation of $\varphi_u$ as

$$\varphi_L^S = (p^T p)^{-1} p^T \tilde{q}_u.$$  \hfill (57)

**C. Estimation of Distances**

With the estimated AoAs $\{\hat{\varphi}_u\}$ and $\{\hat{\omega}_u\}$, we reformulate the array response as

$$a_R(\hat{\omega}_u, \hat{\varphi}_u, d_u^d) = \text{diag} \{p_u(\hat{\omega}_u, \hat{\varphi}_u)\} q_u(\hat{\omega}_u, \hat{\varphi}_u, d_u^d),$$  \hfill (58)

where we define

$$p_u(\hat{\omega}_u, \hat{\varphi}_u) = \left[ \exp \left( -j \frac{2\pi}{\lambda} J_{-N_0} \right), \ldots, \exp \left( -j \frac{2\pi}{\lambda} J_{N_0} \right) \right]^T,$$

$$q_u(\hat{\omega}_u, \hat{\varphi}_u, d_u^d) = \left[ \exp \left( -j \frac{\pi Q_{-N_0}}{\lambda d_u^d} \right), \ldots, \exp \left( -j \frac{\pi Q_{N_0}}{\lambda d_u^d} \right) \right].$$

Note that $J_m$ is given by (17), and $Q_m$ is given by (21) with the estimated $\hat{\omega}_u, \hat{\varphi}_u$. The index $m$ was given by (3).

Similar to (40) and (43), we divide the matrix $A$ and its covariance matrix $R$ into two partitions as $A^H = [A^H_1, A^H_2]$ and $R^H = [R^H_1, R^H_2]$ respectively, where $A_1, R_1 \in \mathbb{C}^{U \times N_R}$ collects the first $U$ rows and $A_2, R_2 \in \mathbb{C}^{(N_R - U) \times N_R}$ contains the remaining $(N_R - U)$ rows. As $A_1$ and $R_1$ are of full rank $U$, the rows of $R_2(A_2)$ can be expressed as a linear combination of linear independent rows of $R_1(A_1)$ with the $U \times (N_R - U)$ linear operator $P_2$. Similar to (42)–(44), one obtains

$$P_2^H A_1 = A_2, P_2^H R_1 = R_2.$$  \hfill (59)

Then, $P_2$ is given by

$$P_2 = (R_2 R_2^H)^{-1} R_1 R_2^H.$$  \hfill (60)

Defining $Q_p^H = [P_p^H, -I_{N_R - U}]$, the orthogonal projector of $A$ is given by

$$Q_p^H A = 0, \Pi_p \triangleq Q_p (Q_p^H Q_p)^{-1} Q_p^H.$$  \hfill (61)
Then, similar to (48), we have the following distance estimation problem
\[ d_{u}^{*} = \min_{d_u} f(d_u) \]
\[ = \min_{\phi_u} \left\{ \sin(\phi_u) \right\} \Pi_p(\sin(\phi_u)) \] (62)

Then, the distance can be estimated by conducting one-dimensional search in the interval \([d_{\text{min}}, d_{\text{max}}]\). The maximal \(U\) largest peaks of the searching results are readily obtained as the estimated distances.

D. Estimation of Channel Gains and Locations

The channel fading coefficients on each sub-band can be estimated through the LS method. With the obtained steering vectors, we reformulated (28) of sub-band \(i\) as
\[ y_{t,i} = G_{\text{RIS},i} \hat{A}_i \text{diag}(g_i) x_t + n_t \] (63)
\[ = G_{\text{RIS},i} \hat{A}_i \text{diag}(g_i) g_i + n_t \] (64)
\[ \triangleq G_i g_i + n_t, \] (65)
where \( \hat{A}_i = [a_{R}^{N-i} (\theta_{u,i}, \phi_{u,i}, d_{0,i}), \ldots, a_{U}^{N-i} (\theta_{u,i}, \phi_{u,i}, d_{0,i})] \), and \( g_i = [g_{1,i}, \ldots, g_{U,i}]^T \). Then, the LS method can be applied to estimate the channel gain of sub-band \(i\) as
\[ g_i = \hat{G}_i y_{t,i}. \] (66)

Note that estimations of location parameters can be conducted in different sub-bands independently, and we denote the estimated AoAs and distances on sub-band \(i\) as \( \theta_{u,i}, \phi_{u,i}, d_{0,i} \). Thus, to obtain the position of UE \(u\) denoted as \( \chi_u = [x_u, y_u, z_u]^T \), according to the geometric relationship with RIS position \((x_R, y_R, z_R)\), we have
\[ x_u \sin \hat{\theta}_{u,i} - y_u \cos \hat{\theta}_{u,i} = \zeta_{u,i}[1] \] (67)
\[ x_u \cos \hat{\theta}_{u,i} + y_u \sin \hat{\theta}_{u,i} = \zeta_{u,i}[2] \] (68)
\[ z_u = \zeta_{u,i}[3] \] (69)
where the vector \( \zeta \) is with size \(3 \times 1\), and \( \zeta_{u,i}[1] = x_0 \sin \theta_{u,i} - y_0 \cos \theta_{u,i}, \zeta_{u,i}[2] = d_{0,i}^2 \cos \phi_{u,i} + x_0 \cos \phi_{u,i} + y_0 \sin \phi_{u,i}, \zeta_{u,i}[3] = z_0 - d_{0,i}^2 \sin \phi_{u,i}. \)

Thus, we can collect the equations from all the sub-bands to obtain the final estimations of UE locations. However, considering the frequency-selective fading in THz bands, we introduce the channel weight to account for the estimation results over the different frequency bands, i.e. \( \eta_t = \frac{|g_t|}{\sum_{i=1}^{U} |g_t|} \). Thus we have the following equation
\[ \Upsilon_{u} \chi_{u} = \zeta_{u}, \] (70)
where
\[ \Upsilon_{u} = [\eta_1 \Upsilon_{u,1}, \ldots, \eta_T \Upsilon_{u,T}], \quad \zeta_u = [\zeta_{u,1}, \ldots, \zeta_{u,T}], \quad \Upsilon_{u,i} = \begin{bmatrix} \sin \hat{\theta}_{u,i} & -\cos \hat{\theta}_{u,i} & 0 \\ \cos \hat{\theta}_{u,i} & \sin \hat{\theta}_{u,i} & 0 \\ 0 & 0 & 1 \end{bmatrix}. \] (71)

Then, the location of the UE \(u\) is given by
\[ \chi_{u,i} = (\Upsilon_{u})^{-1} \zeta_u. \] (72)

Algorithm 1: Near Field Joint Channel Estimation and Localization (NF-JCEL) Algorithm.

**Input:** The received signal \(y_{t,i}\) of each sub-band; pilot data \(x_t, t = 1, \ldots, \tau\).

**Output:** The AoAs of the RIS-UE links \(\omega_u, \phi_u\); The distance \(d_{u}^{*}\) of the \(u\)-th RIS-UE link; The channel fading \(g_i\) on each sub-band; The UE locations \((x_u, y_u, z_u)\);

1: Estimate array covariance matrix \(\hat{R}\) according to (31);
2: Construct matrix \(\hat{T}\) according to (38);
3: Calculate AoAs \(\omega_u\) and \(\phi_u\) by solving Problem (49), where the optimal \(\omega_u^{*}\) is obtained according to (55) and the estimated \(\phi_u\) is obtained according to (57);
4: Search optimal distance \(d_{u}^{*}\) by solving Problem (62);
5: Calculate locations \((x_u, y_u, z_u)\) according to (72);
6: Obtain the channel fading coefficients \(g_i\) by using the LS method.

### IV. SIMULATION RESULTS

In this section, representative simulation results are presented for performance validation.\(^2\) In simulations, UEs are distributed in a 5 m \(\times\) 5 m square area. The simulation parameters are summarized in Table I. Unless specified otherwise, the RIS panel is equipped with 2873 reflecting elements, the number of RIS training phase shift vectors is \(S = 140\), the number of pilot data is \(\tau = 5\). In the THz band, the absorbent molecules coefficient \(K(f_i)\) is simulated according to a simplified molecular absorption coefficient model for 200 – 400 GHz frequency band [55], which has two major absorption peaks at 325 GHz and 380 GHz. For performance comparison, we utilize the conventional far-field model as the performance benchmark, which is labeled as “FF”. UEs are supposed to be on the XOY plane, i.e., \(z_u = 0\), as in this case, the far-field method can only obtain the 2D localization. The proposed NF-JCEL algorithm is labeled as “Prop”.

#### A. Impact of Number of RIS Elements

Figs. 7–9 show the RMSE performances as functions of the numbers of reflecting elements, where the Fraunhofer distance corresponding to the number of reflecting elements is from 0.07 m to 6.2 m. The number of UE is 2, one is a close UE

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\(^2\)Considering the necessity of a thorough bias analysis to ensure accurate CRLB analysis, which needs further careful attention, we evaluate the effectiveness of the proposed algorithm with RMSE in this work.
and the other is a far UE, resulting in three RMSE curves: the respective RMSEs of these two UEs and the sum of two RMSEs, which are labeled as “RMSE of near UE”, “RMSE of far UE” and “Sum-RMSE”, respectively. Unless specified otherwise, the same configuration and labels are adopted in the following subsections.

It can be seen from Fig. 7 that the proposed algorithm outperforms the corresponding far-field cases, and the performance gap increases with the number of reflecting elements. This is due to the fact that more reflective array elements can provide higher angular resolution, which leads to sharper correlation peaks, i.e., the objective in (55). As for the far-field case, the impact of the spherical wavefront propagation becomes more significant, which is neglected in the comparison “FF” algorithm. In this case, the approximation error of the plane wave becomes even more severe, although correlation matrices of larger dimensions can be exploited. Overall, the two different trends are caused by the different channel models adopted by these two different algorithms.

Fig. 8 shows the RMSEs of the estimated AoA $\omega_u = \sin \phi_u$. It can be seen from Fig. 8 that the sum-RMSE of the proposed algorithm decreases with increasing the number of reflecting elements, while the sum-RMSE of the far-field algorithm increases with the number of reflecting elements. This means that the near-field effect increases with increasing the number of reflecting elements, i.e. the panel size of RIS. To be more specific, the channel model approximation error of the far-field algorithm increases with the number of reflecting elements. Fig. 9 shows the RMSEs of the estimated AoA $\varphi_u = \sin \theta_u \cos \phi_u$. From Fig. 9, similar trends in the sum RMSE can be observed to those from Fig. 8.

Fig. 10 shows the RMSE performance of channel fading gain. In Fig. 10, it is observed that the best RMSE of the proposed algorithm is that on the sub-band centered at $f_c = 320$ GHz, as the channel fading is not so severe compared with the other two sub-bands. For the far-field algorithms, the RMSE on the sub-band centered at $f_c = 325$ GHz is the worst as the channel fading on this sub-band suffers from a large molecular absorption coefficient. Fig. 11 shows the RMSE performance of the estimated distances on different sub-bands, where the searching interval is given by $[d_{\min} = 0.1 \text{ m}, d_{\max} = 7.1 \text{ m}]$. As the far-field algorithm cannot provide direct distance estimation, only the results obtained by the proposed algorithm are displayed. Similar trends to Fig. 10 can be seen in Fig. 11.

**B. Impact of Number of UEs**

Fig. 12 shows the localization performance by presenting three RMSE curves: the average RMSE of UEs, the RMSE
of nearest UE and the best RMSE of two RMSEs, which are labeled as “avg RMSE”, “nearest RMSE” and “best RMSE”, respectively. It is observed that, as the number of users increases, the average RMSE of the proposed algorithm also increases due to the limited simulated area. With more users, their angular separation decreases, resulting in confusion of estimates among different users. Also, it is interesting to see that nearest user not always obtains the best RMSE. Meanwhile, in the far-field case, it is observed that the best RMSE decreases with the number of UEs, but the proposed algorithm shows better performance than the far-field algorithm. This is because the added UE is gradually far away from RIS panels so that the near field effect gradually becomes insignificant. Fig. 13 shows the RMSE performance of the channel fading coefficients with respect to the number of UEs. Similar trends to Fig. 12 can be seen in Fig. 13. Also, similar to Fig. 10, best channel fading RMSE of the proposed algorithm was observed on the sub-band centered at \( f_c = 320 \) GHz.

### C. Impact of RIS Phase Shifts

Fig. 14 illustrates a comparison of the RMSE for location estimation obtained by different patterns of RIS phase shifts. To perform a comprehensive comparison, we set up three patterns of RIS training phase shifts: 1) Directly taking the first \( S \) columns of the DFT matrix, labeled as “DFTPhase”; 2) Evenly taking \( S \) columns in the DFT matrix according to the linear angle interval, labeled as “GridDFT”; and 3) Randomly generating the phase of each reflecting element from \([0, 2\pi)\), labeled as “RandPhase.” It is noteworthy that the “RandPhase” pattern exhibits superior performance compared to the other two cases, especially when the number of RIS training phase shift vectors, i.e. \( S \), is less than 100. When the number of training phase shifts \( S \geq 120 \), the performance gaps of the three schemes become small. This phenomenon occurs due to the fact that a DFT matrix of size \( N_R \) produces a grid of angles spaced at \( \frac{2\pi}{N_R} \). When the number of training phases is small, the angles of the training phases in the DFT scheme and the linear interval scheme are limited. For instance, when \( S = 80 \), the maximum angle obtained in the DFT scheme is \( \frac{80 \times 2\pi}{2873} \), which does not exceed \( \pi/2 \), and thus fails to cover the angles of some UEs. However, the randomly generated phases in “RandPhase” pattern are more likely to cover the direction angle of the user. Therefore, unless otherwise specified, the “RandPhase” pattern is utilized in the subsequent simulation setup.

Fig. 15 shows the impact of the number of RIS training phase shift vectors on the RMSE performance. The RMSE of locations obtained by the proposed algorithm decreases rapidly when the number of training phase shift vectors increases to 120. Then, the decent speeds of RMSE slow down for the proposed
V. CONCLUSION

In this article, we have investigated the localization and CSI estimation scheme for the near-field THz system with RIS. The following conclusions are drawn:

- The proposed NF-JCEL algorithm shows attractive performance in terms of localization and CSI estimation RMSE, especially for the near-field transmission introduced by the XL-RIS panel. Meanwhile, the conventional far-field model shows severe performance degradation in the near-field channel.
- The complexity in the near-field CSI estimation is highly dependent on the array steering vector formulation, where the UE distance and the AoAs are different by reflecting elements and jointly coupled together. However, this also leads to higher resolution accuracy. Thus, the near-field channel model can provide 3D localization with a single RIS panel, which is not applicable for the far-field model with one RIS panel in the same case.
- The localization accuracy is also highly dependent on the angle separations between different UEs, which can be improved with a large RIS panel with more elements. However, without considering the near-field effect, the more reflecting elements cannot bring more benefits but severe performance degradation. Thus, it is a necessity to consider the spherical wavefront feature for the high precision localization system.

In future work, it would be valuable to further analyze the error distribution of the proposed algorithm in order to obtain performance limits such as the CRLB, which would enable a more comprehensive performance evaluation.

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