ABSTRACT Holographic massive multiple-input multiple-output (MIMO), in which a spatially continuous surface is being used for signal transmission and reception, has emerged as a promising solution for improving the coverage and data rate of wireless communication systems. To realize these objectives, the acquisition of accurate channel state information in holographic massive MIMO systems is crucial. This paper proposes a channel estimation scheme based on a parametric physical channel model for line-of-sight (LoS) dominated communication in millimeter and terahertz wave bands. The proposed channel estimation scheme exploits the specific structure of the radiated beams generated by the continuous surface to estimate the channel parameters in a dominated LoS channel model. Since the number of unknown channel parameters is fixed regardless of the number of antennas, the training overhead of the proposed scheme does not scale with the number of antennas. The simulation results demonstrate that the proposed estimation scheme significantly outperforms other benchmark schemes in a poor scattering environment.

INDEX TERMS Channel estimation, holographic massive MIMO, millimeter-wave and terahertz communication, beyond massive MIMO, parametric channel model.

I. INTRODUCTION

The millimeter-wave (mmWave) and terahertz (THz) frequency bands will play a pivotal role in next-generation (e.g., beyond 5G) wireless networks since they would be able to provide abundant spectrum resources, higher data rates, and lower latency [1], [2]. However, severe path-loss, atmospheric absorption, human blockage, and other environmental obstruction are key challenges for enabling wireless communication in the mmWave and THz bands [3], [4]. Over the past few years, massive multiple-input multiple-output (MIMO) communication systems, in which base stations (BSs) are equipped with a large antenna array, have been introduced to provide beamforming gains that can overcome the mentioned limitations [5], [6]. Since the beamforming gain of massive MIMO increases with the number of antennas, it would be highly desirable to have as many antennas as possible that are compactly arranged [7], [8]. In this direction, spatially continuous apertures with densely deployed antennas, known as holographic massive MIMO [8] and large intelligent surfaces (LISs) [9], were introduced to go beyond massive MIMO systems [10], [11], [12], [13], [14], [15], [16]. Since these continuous apertures can be seen as an extension of traditional massive MIMO from a discrete array to a continuous surface [16], they have been referred to as holographic massive MIMO [3], [8].

The holographic massive MIMO that comprises a massive number of phase-shifting elements with steerable beamforming weight can be used for generating narrow beams with high beamforming gains [11]. Moreover, in the holographic massive MIMO, multiple radio frequency (RF) chains can be connected to the aperture to enable spatial multiplexing [8], [11]. The existing research works have verified the effect of the holographic massive MIMO systems on enhancing the communication performance in various scenarios under the assumption of the availability of perfect channel state information (CSI) [15], [16], [17], [18]. To achieve the full potential of the holographic massive MIMO systems, acquiring accurate CSI is a fundamental and challenging task in practice. Since the holographic massive MIMO consists of a
A. RELATED WORK

Up to now, a variety of channel estimation schemes have been proposed for the massive MIMO communication systems, including exhaustive search [19], hierarchical search [20], [21], [22], [23], and compressed sensing (CS) [24], [25], [26], [27], [28], [29], [30], [31], [32]. The authors in [19] propose the exhaustive search algorithm as a straightforward approach where the transmitter and receiver scan all possible angular directions to find the best pair of AoA and AoD. However, the training overhead of the exhaustive search approach is prohibitively high, especially when a large number of antennas generate narrow beams in the mmWave and THz frequency bands. To improve the efficiency of the exhaustive search, the hierarchical search based on a predefined codebook was proposed in [20], [21], [22], and [23]. In the first stage of the hierarchical search, the codewords with larger beam widths are used to scan the entire angular domain. Then, in the second stage, codewords with narrower beam widths are used to scan only a specific range obtained in the first stage. In [20], a hierarchical codebook is designed, where sub-array and deactivation antenna processing techniques were exploited to generate the codebook via closed-form expressions. However, turning off some antennas may not be a good approach since the reduced array gain has an undesirable effect on the performance [21]. The authors in [22] design multi-resolution beamforming sequences to quickly search out the dominant channel direction. Reference [23] proposes a beam training method based on a dynamic hierarchical codebook to estimate the mmWave massive MIMO channel with multi-path components. However, the accuracy of the hierarchical search is limited by the codebook size. Moreover, all these hierarchical schemes may incur high training overhead and system latency because they require non-trivial coordination between the transmitter and the receiver.

At mmWave frequency, typically, only a few dominant path components contribute to the received power, i.e., mm-wave channels are sparse in the angular domain. Thereby, different compressed sensing (CS) methods exploit the sparsity of the mmWave channels to estimate the channel with relatively few measurements despite a large number of phase-shifting elements [24], [25], [26], [27], [28], [29], [30], [31], [32]. In the CS-based channel estimation, first, a set of random training sequences is used to measure the channel. Then, a sparse recovery algorithm is employed to obtain the path parameters. The CS-based channel estimation schemes can be classified into two main categories: on-grid and gridless estimation. The on-grid schemes assume that the angle of arrivals (AoAs) and angle of departures (AoDs) are discrete with finite resolutions. However, the actual angles are continuous in practice [24], [25], [26], [27], [28]. The accuracy of these schemes depends on the quantization resolution as well as the number of measurements [29]. As a result, the training overhead can be significantly high to achieve satisfactory accuracy. On the other hand, the gridless schemes deal directly with the continuous domain without imposing a discrete dictionary [30], [31], [32]. The gridless schemes increase estimation accuracy at the expense of increased computational complexity. None of these channel estimation schemes has been explicitly designed for channels dominated by a line-of-sight (LoS) path. The question that we would like to answer in this paper is, what if the channel is dominated by a LoS path? Answering this question is important because, in mmWave and THz communications, the channel is sparse and LoS dominant.

In the user localization problem, the parametric channel model is used to estimate the distance of the user from the BS and the elevation and azimuth AoD [33], [34]. Thereby, the channel estimation problem and user localization are highly correlated [35], [36]. Different from the studies on localization problems [37], [38], [39], [40], [41], [42], in this work, we circumvent the estimation of the distance to obtain a closed-form solution for the channel estimation problem for channels dominated by a LoS path.

B. MAIN CONTRIBUTIONS

In this paper, we focus on channels that are comprised of a LoS path, and aim at developing a channel estimation strategy that fully exploit the structure of the radiated pattern to significantly reduce the channel estimation overhead. Different from the aforementioned works, we obtain a closed-form solution for the channel estimation problem based on a parametric channel model. The training overhead and the computational complexity of the proposed scheme do not scale with the number of antennas. Specifically, our main contributions are as follows.

- Based on the parametric channel model, we simplify the BS-user channel in the far-field region of the BS. We show that the LoS component of the channel can be written in terms of sinc functions for linear phase shift profiles at the aperture. We show that only two parameters are required to be estimated, including the elevation and azimuth AoD.
- We exploit the specific structure of the radiated beams generated by the aperture to propose an iterative algorithm. Since the performance of the proposed iterative algorithm depends on the initial values of the algorithm, we propose a simple method to provide initial values using three pilot signals.
- For the near-field of the BS, we partition the continuous aperture into tiles such that the far-field condition holds for each tile [43]. Then, the channel in the near-field is modeled as the superposition of the channels through the individual tiles. Since the channel between each tile and the user can be written in terms of sinc functions, we can apply the proposed iterative algorithm to estimate the unknown parameters of each tile.
We numerically demonstrate that the proposed estimation scheme significantly outperforms other benchmark schemes.

The remaining part of this paper is organized as follows. In Sec. II, the system model is described. In Sec. III, we propose our estimation scheme in the case without and with receiver noise. Then, we extend the proposed scheme to the near-field region of the aperture in Sec. IV. The simulation results are provided in Sec. V. Finally, Sec. VI concludes the paper.

II. SYSTEM MODEL

In this section, we introduce the system and channel models.

A. SYSTEM MODEL

We consider a holographic massive MIMO system where a BS equipped with a rectangular aperture serves multiple users with a single antenna, see Fig. 1. For data communication, multiple RF chains can be used at the BS to transmit and receive a superposition of beams to serve multiple users using spatial multiplexing. However, we use only one of these RF chains at the BS for the channel estimation. We assume that the users transmit orthogonal pilot symbols used for the channel estimation at the BS.

As shown in Fig. 1, the size of the rectangular aperture is \( L_x \times L_y \), where \( L_x \) and \( L_y \) are the width and the length of the aperture, respectively. The aperture is comprised of a large number of sub-wavelength phase-shifting elements of size \( L_e \times L_e \) that can change the phase of the signal. We assume that the aperture lies in the \( x - y \) plane of a Cartesian coordinate system, and its center is placed at the origin of the coordinate system, see Fig. 1. Let \( d_r \) be the distance between neighboring phase-shifting elements. The total number of phase-shifting elements of the aperture is given by \( M = M_x \times M_y \), where \( M_x = L_x / d_r \) and \( M_y = L_y / d_r \).

In the uplink communication direction, the baseband received signal at the BS, denoted by \( y \), can be expressed as follows:

\[
y = \text{vec} \left( \Gamma \right)^T \left( \text{vec} \left( H \right) x + n \right),
\]

where \( \Gamma \in \mathbb{C}^{M_y \times M_x} \) is the beamforming weight matrix at the BS, \( H \in \mathbb{C}^{M_y \times M_y} \) is the channel matrix from the user to the phase-shifting elements, \( x \) is the transmitted signal from the user, and the vector \( n \in \mathbb{C}^{M_y \times 1} \) represents the Additive White Gaussian Noise (AWGN) that is distributed as \( \mathcal{CN}(0, \sigma_n^2 I_M) \).

B. FAR-FIELD CHANNEL MODEL

In this subsection, we provide the far-field channel model between the BS and the users based on the path parameters of the system. Since the users send orthogonal pilot symbols for channel estimation, we model the channel between the BS and a typical user. In the antenna array terminology, the far-field is referred to as the condition that the maximum phase error of the received signal on the antenna array does not exceed \( \frac{\pi}{8} \) [49]. Based on this definition, the far-field region of the BS is obtained as

\[
d_0 \geq \frac{2 \left( L_x^2 + L_y^2 \right)}{\lambda},
\]

where \( d_0 \) denotes the distance between the user and the center of the aperture, and \( d_F = \frac{2 \left( r_0^2 + r_2^2 \right)}{\lambda} \) is referred to as the Fraunhofer distance [48].

In addition to the LoS channel between the BS and the user, there are \( Q \) scatters, where each scatter is assumed to contribute a single propagation path between the BS and the user. Therefore, the BS-user channel consists of one LoS and \( Q \) non-LoS (NLoS) components. Let \( \theta_0 \in [0, \pi] \) and \( \phi_0 \in [0, 2\pi] \) denote the elevation and azimuth angles of the impinging wave from the user to the center of the aperture through the LoS path, see Fig. 1. Similarly, \( \theta_q \in [0, \pi] \) and \( \phi_q \in [0, 2\pi] \) represent the elevation and azimuth angles of the impinging wave from the user to the center of the aperture through the \( q \)-th scatter. In addition, let \( h_0 \) and \( h_q \) denote the

![Fig. 1. Schematic illustration of the holographic MIMO transceiver. Each phase-shifting element of the aperture changes the phase of the RF signal, and hence the BS is able to receive/send a beamformed signal from/towards the users.](image)
complex channel gain of the LoS path and the $q$-th NLoS path. Under the far-field condition, the channel matrix between the user and the aperture is given by

$$
H = h_0 A(\phi_0, \theta_0) + \sum_{l=1}^{Q} h_q A(\phi_q, \theta_q),
$$  

(3)

where $A(\phi, \theta), \forall \phi \in [0, 1, \ldots, Q]$, denotes the array response matrix at the angle of arrival $\phi$ and $\theta$. Assuming $M_x$ and $M_y$ are odd positions, the number of the $(m_x, m_y)$-th phase-shifting element is given by $(x, y) = (m_x d_r, m_y d_r)$ for $m_x = -\frac{M_x-1}{2}, \ldots, \frac{M_x-1}{2}$ and $m_y = -\frac{M_y-1}{2}, \ldots, \frac{M_y-1}{2}$. The $(m_x + M_x + 1, m_y + M_y + 1)$-th entry of $A(\phi, \theta)$ is given by

$$
\left[ A(\phi, \theta) \right] (m_x + M_x + 1, m_y + M_y + 1) = e^{jk_0 d_r (m_x \sin(\phi) \cos(\theta) + m_y \sin(\theta) \sin(\phi))},
$$  

(4)

where $k_0 = 2\pi / \lambda$ is the wave number, $\lambda$ is the wavelength of the carrier frequency. In (3), the complex channel gain of the LoS path, $h_0$, is given by

$$
h_0 = \frac{\lambda \sqrt{F}}{4\pi d_0} e^{-jk_0 d_0},
$$  

(5)

where $F$ accounts for the effect of the size and power radiation pattern of the phase-shifting elements on the channel gain. Finally, the complex channel gain of the $q$-th NLoS path, $h_q$, is given by

$$
h_q = \zeta_q PL(d_q),
$$  

(6)

where $\zeta_q$ is the small-scale fading of the aperture-user channel through the $q$-th scatter, and $PL(.)$ is the channel path loss function.

Due to severe path-loss at the mmWave and THz frequency bands, the power of the LoS component is much higher than the power of the NLoS components [45], [46]. In fact, it is less likely to build effective communication via NLoS components in the presence of a strong LoS link [47]. Thereby, we focus on the LoS component to consider as an interference term and investigated in the Numerical Results section.

Each phase-shifting element at the aperture can be configured to impose different phase shifts on the transmitted and received signal [11]. The $(m_x + M_x + 1)$-th row and $(m_y + M_y + 1)$-th column of $H$ in (1), represents the beamforming weight at the $(m_x, m_y)$-th phase-shifting element and can be written as

$$
\Gamma(m_x + M_x + 1, m_y + M_y + 1) = \frac{1}{\sqrt{M}} e^{j\beta_{m_x, m_y}},
$$  

(10)

where $\beta_{m_x, m_y}$ is the phase shift at the $(m_x, m_y)$-th element. For ease of presentation, let us define the phase shift parameters of the aperture for all elements as $\beta = \{\beta_{m_x, m_y} \mid m_x, m_y\}$. Finally, to obtain a more compact expression for the received signal in (1), we define the effective BS-user LoS channel as $G(\beta) \triangleq \text{vec} (\Gamma)^T \text{vec} (H_{(\text{LoS})})$, which can be written as

$$
G(\beta) = \sum_{m_x=-\frac{M_x-1}{2}}^{\frac{M_x-1}{2}} \sum_{m_y=-\frac{M_y-1}{2}}^{\frac{M_y-1}{2}} \frac{\Gamma(m_x + M_x + 1, m_y + M_y + 1)}{\sqrt{M}} \times \frac{\text{vec}(H_{(\text{LoS})})}{\text{vec}(H_{(\text{LoS})})}
$$
$$
\times e^{j(k_0 d_r (m_x \alpha_1 + m_y \alpha_2) + \beta_{m_x, m_y})},
$$  

(11)

where

$$
\alpha_1 = \sin(\theta_0) \cos(\phi_0),
$$  

(8)

$$
\alpha_2 = \sin(\theta_0) \sin(\phi_0).
$$  

(9)

It can be observed from (11) that $G(\beta)$ attains its maximum value when we set

$$
\beta_{m_x, m_y} = -\text{mod}(k_0 d_r (m_x \alpha_1 + m_y \alpha_2), 2\pi), \quad \forall m_x, m_y.
$$  

(12)

From (12), we can conclude that to obtain the optimal phase shift for maximizing the effective BS-user channel in the far-field region of the BS, we need to estimate only two parameters, $\alpha_1$ and $\alpha_2$. Since we do not have the values of $\alpha_1$ and $\alpha_2$, we consider a general case to see the BS-user channel in the far-field of the BS if we replace $\alpha_1$ and $\alpha_2$ with any other values. In the following lemma, we apply a linear phase shift to each phase-shifting element to obtain a closed-form expression for the effective BS-user channel in the far-field of the BS.

**Lemma 1:** If we apply the following linear phase shift across the aperture elements, i.e., to the $(m_x, m_y)$-th element

$$
\beta_{m_x, m_y} = -\text{mod}(k_0 d_r (m_x \beta_1 + m_y \beta_2), 2\pi), \quad \forall m_x, m_y.
$$  

(13)
then the effective BS-user channel in the far-field region of the aperture is a function of $\beta_1$ and $\beta_2$ and can be obtained as

$$G(\beta_1, \beta_2) \approx \left( \frac{\lambda e^{-jk_0d_0}}{4\pi d_0} \times \sqrt{F} \right) \times \left( \sin \left( \frac{kd_x}{2} (\alpha_1 - \beta_1) \right) \sin \left( \frac{kd_y}{2} (\alpha_2 - \beta_2) \right) \right) \times \left( \sin \left( \frac{kd_x}{2} (\alpha_1 - \beta_1) \right) \sin \left( \frac{kd_y}{2} (\alpha_2 - \beta_2) \right) \right),$$

(14)

Proof: The proof follows similar steps as [42, and 47, Ch. 6] and is provided in Appendix A for completeness. □

For the extremely sub-wavelength elements ($d_r \to 0$), the aperture acts as a continuous surface [10], [43]. Assuming $d_r \to 0$, we can approximate $\sin \left( \frac{kd_x}{2} (\alpha_1 - \beta_1) \right)$ and $\sin \left( \frac{kd_y}{2} (\alpha_2 - \beta_2) \right)$ in the denominator of (14) with $\frac{kd_x}{2} (\alpha_1 - \beta_1)$ and $\frac{kd_y}{2} (\alpha_2 - \beta_2)$, respectively. In addition, this approximation is more accurate when $\beta_1$ and $\beta_2$ are close to $\alpha_1$ and $\alpha_2$, respectively. Then, the effective BS-user channel in the far-field of the BS in (14) can be written as

$$G(\beta_1, \beta_2) \approx \left( \frac{\lambda e^{-jk_0d_0}}{4\pi d_0} \times \sqrt{F} \right) \times \sin \left( \frac{kd_x}{2} (\alpha_1 - \beta_1) \right) \sin \left( \frac{kd_y}{2} (\alpha_2 - \beta_2) \right),$$

(15)

where $\sin(x) = \frac{\sin(x)}{x}$. According to (15), the absolute value of the BS-user channel would be maximized when the sinc functions attain their maximum value, which occurs for the first and second sinc functions when $\beta_1$ and $\beta_2$ are set as $\beta_1 = \alpha_1$ and $\beta_2 = \alpha_2$, respectively. Therefore, when we use the far-field channel model, we only need to estimate two parameters, $\alpha_1$ and $\alpha_2$. In Sec. III, we exploit the properties of these two sinc functions to propose the channel estimation scheme.

III. PROPOSED CHANNEL ESTIMATION

Now that we have identified the parameters that need to be estimated in the far-field region of the aperture, we move towards proposing our scheme for their estimation by exploiting the specific structure of the radiated beam in the dominated LoS channel model. Specifically, to obtain some intuition, we first propose the channel estimation scheme under the assumption that there is no noise in the system. Once we obtain the intuitions, we propose an iterative algorithm for the channel estimation in the presence of noise.

A. CHANNEL ESTIMATION IN THE ABSENCE OF NOISE

In this subsection, we propose the channel estimation scheme in the absence of noise to provide some intuitions, which is a widely adopted approach in literature [32], [47], [51]. The study of the noise-less case (albeit not practical) reveals the key features of the radiated pattern exploited here for channel estimation and sets the basis for the proposed estimator in the noisy case. In the channel estimation procedure, the user sends pilot signals $x_p = \sqrt{P_p}$ to the BS, where $P_p$ is the pilot transmit power. In the absence of noise, the received signal at the BS is given by

$$y(\beta_1, \beta_2) = \sqrt{P_p} \times G(\beta_1, \beta_2).$$

(16)

Substituting (15) into (16) and assuming $L_x = K_x \lambda$ and $L_y = K_y \lambda$, where $K_x, K_y \in \mathbb{N}$ are integer numbers, the absolute value of the received signal at the BS is given by

$$\left| y(\beta_1, \beta_2) \right| \approx \frac{\lambda}{4\pi d_0} \sqrt{F} \frac{\sqrt{P_p} M}{\sin \left( K_x \pi (\alpha_1 - \beta_1) \right) \sin \left( K_y \pi (\alpha_2 - \beta_2) \right)}.$$

(17)

In the following, we show that $\alpha_1$ and $\alpha_2$ can be estimated using five pilots sent by the user. Before sending each pilot, the BS applies a new phase shift to the elements by changing $\beta_1$ and $\beta_2$ in (13). For the first pilot, the BS sets $\beta_1 = \hat{\beta}_1$ and $\beta_2 = \hat{\beta}_2$, where $\hat{\beta}_1$ and $\hat{\beta}_2$ are two random numbers in the range of $-1$ to $1$. Note that, according to (8) and (9), $\alpha_1$ and $\alpha_2$ are in the range of $-1$ to $1$. Then, the absolute value of the received signal at the BS due to the first pilot signal is given by

$$\left| y(\hat{\beta}_1, \hat{\beta}_2) \right| \approx \frac{\lambda}{4\pi d_0} \sqrt{F} \frac{\sqrt{P_p} M}{\sin \left( K_x \pi (\alpha_1 - \hat{\beta}_1) \right) \sin \left( K_y \pi (\alpha_2 - \hat{\beta}_2) \right)}.$$

(18)

For the second pilot, the BS sets $\beta_1 = \hat{\beta}_1 + \nu$ and $\beta_2 = \hat{\beta}_2$, where the value of $\nu$ will be discussed later. Therefore, the absolute value of the received signal at the BS is

$$\left| y(\hat{\beta}_1 + \nu, \hat{\beta}_2) \right| \approx \frac{\lambda}{4\pi d_0} \sqrt{F} \frac{\sqrt{P_p} M}{\sin \left( K_x \pi (\alpha_1 - \hat{\beta}_1 - \nu) \right) \sin \left( K_y \pi (\alpha_2 - \hat{\beta}_2) \right)}.$$

(19)

If the BS divides (18) by (19), it will obtain

$$\left| \frac{y(\hat{\beta}_1, \hat{\beta}_2)}{y(\hat{\beta}_1 + \nu, \hat{\beta}_2)} \right| \approx \frac{\sin \left( K_x \pi (\alpha_1 - \beta_1) \right)}{\sin \left( K_x \pi (\alpha_1 - \beta_1 - \nu) \right)} \frac{\sin \left( K_y \pi (\alpha_2 - \beta_2) \right)}{\sin \left( K_y \pi (\alpha_2 - \hat{\beta}_2) \right)}.$$

(20)
If \( v \) is selected such that \( K_x v \in \mathbb{N} \), we have
\[
\sin(K_x \pi (\alpha_1 - \hat{\beta}_1 - v)) = \sin(K_x \pi (\alpha_1 - \hat{\beta}_1)).
\] (21)

Using (21), we can simplify (20) to
\[
\frac{y(\hat{\beta}_1 + v, \hat{\beta}_2)}{y(\hat{\beta}_1, \hat{\beta}_2)} \approx \left| \frac{\alpha_1 - \hat{\beta}_1 - v}{\alpha_1 - \hat{\beta}_1} \right|.
\] (22)

From equation (22), two solutions for \( \alpha_1 \), denoted by \( \alpha_1^{(1)} \) and \( \alpha_1^{(2)} \), can be obtained as
\[
\alpha_1^{(1)/(2)} = \hat{\beta}_1 + \frac{y(\hat{\beta}_1 + v, \hat{\beta}_2)}{y(\hat{\beta}_1, \hat{\beta}_2)} v.
\] (23)

In order to identify the correct solution for \( \alpha_1 \), the third pilot signal should be sent from the user. For the third pilot signal, the BS sets. Using the received signal of the first and third pilot signals, two other solutions for \( \alpha_1 \), denoted by \( \alpha_1^{(3)} \) and \( \alpha_1^{(4)} \), can be similarly obtained as
\[
\alpha_1^{(3)/(4)} = \hat{\beta}_1 + \frac{y(\hat{\beta}_1 - v, \hat{\beta}_2)}{y(\hat{\beta}_1, \hat{\beta}_2)} v.
\] (24)

One of the solutions in (23) is approximately the same as one of the solutions in (24). Therefore, using (23) and (24), the correct solution for \( \alpha_1 \) can be obtained as
\[
\alpha_1 \approx \left\{ \frac{\alpha_1^{(i)} + \alpha_1^{(j)}}{2} \mid \min_i |\alpha_1^{(i)} - \alpha_1^{(j)}| ; i \in \{1, 2\}, j \in \{3, 4\} \right\}.
\] (25)

In order to obtain \( \alpha_2 \), two more pilot signals are needed to be sent by the user. For these two pilot signals, the BS sets two different phase shifts as \( (\beta_1, \beta_2) = (\hat{\beta}_1, \hat{\beta}_2 + w) \), \( (\hat{\beta}_1, \hat{\beta}_2 - w) \), where \( w \) is selected such that \( K_x w \in \mathbb{N} \). Then, similar to \( \alpha_1 \), we have the following solutions for \( \alpha_2 \)
\[
\alpha_2^{(1)/(2)} = \hat{\beta}_2 + \frac{y(\hat{\beta}_1, \hat{\beta}_2 + w)}{y(\hat{\beta}_1, \hat{\beta}_2)} w,
\] (26)
\[
\alpha_2^{(3)/(4)} = \hat{\beta}_2 + \frac{y(\hat{\beta}_1, \hat{\beta}_2 - w)}{y(\hat{\beta}_1, \hat{\beta}_2)} w.
\] (27)

Then, using (26) and (27), the correct solution for \( \alpha_2 \) can be obtained as
\[
\alpha_2 \approx \left\{ \frac{\alpha_2^{(i)} + \alpha_2^{(j)}}{2} \mid \min_i |\alpha_2^{(i)} - \alpha_2^{(j)}| ; i \in \{1, 2\}, j \in \{3, 4\} \right\}.
\] (28)

From (25) and (28), we can conclude that when the channel is dominated by LoS path, we can find the unknown parameters without any ambiguity using five pilot signals in the absence of noise.\(^2\)

Remark 1: The random choices for \( \hat{\beta}_1 \) and \( \hat{\beta}_2 \) may lead to the null points of the sinc functions in (18), which occurs at \( \hat{\beta}_1 = \alpha_1 + \frac{\pi}{K_x} \) and \( \hat{\beta}_2 = \alpha_2 + \frac{\pi}{K_x} \), where \( q \in \mathbb{N} \). For these unfortunate initial values, the received signals at the BS are zero; hence, we cannot estimate \( \alpha_1 \) and \( \alpha_2 \). Since the initial values are chosen randomly, the probability of occurrence at the null points of the sinc functions is zero. However, if this happens, we change the initial values from \( \hat{\beta}_1 \) and \( \hat{\beta}_2 \) to \( \hat{\beta}_1 + \frac{1}{2K_x} \) and \( \hat{\beta}_2 + \frac{1}{2K_x} \), respectively, to move from the nulls to their closest peaks.

B. CHANNEL ESTIMATION IN THE PRESENCE OF NOISE

The proposed scheme in the previous subsection perfectly estimates the channel parameters for the ideal case when there is no noise at the receiver. However, that case is only for intuition purposes since noise is always unavoidable in practice. In the presence of noise at the receiver, the estimated values in (25) and (28) have errors. In this section, we utilize the estimation scheme introduced in Sec. III-A to propose an iterative algorithm to decrease the channel estimation error due to the noise.

In the presence of noise, if the user sends the pilot \( x_p = \sqrt{P_p} \) to the BS, the received signal at the BS, denoted by \( \hat{y} \), is given by
\[
\hat{y}(\beta_1, \beta_2) = \sqrt{P_p} \times G(\beta_1, \beta_2) + n,
\] (29)
where \( n \) denotes the additive white Gaussian noise (AWGN) at the BS.

The proposed iterative algorithm for noisy channel estimation is presented in Algorithm 1, in which index \( k \) is used to denote the \( k \)-th iteration. This algorithm works as follows. As the starting point for the iterative algorithm, we choose \( (\hat{\beta}_1^{(0)}, \hat{\beta}_2^{(0)}) \) as a random pair between \([-1, 1]\). In each iteration, the user sends five pilots to the BS. Then, the BS estimates \( \alpha_1 \) and \( \alpha_2 \) based on the received pilots, as follows. In the \( k \)-th iteration, similar to (23) and (24), four solutions
for $\alpha_1$ can be obtained as

$$
\alpha_1^{(1/2)} = \hat{\beta}_1^{(k-1)} + \frac{1}{\kappa} \left[ \tilde{y} \left( \hat{\beta}_1^{(k-1)} + v, \hat{\beta}_2^{(k-1)} \right) + \tilde{y} \left( \hat{\beta}_1^{(k-1)} - v, \hat{\beta}_2^{(k-1)} \right) \right], \\
\alpha_2^{(1/2)} = \hat{\beta}_2^{(k-1)} + \frac{1}{\kappa} \left[ \tilde{y} \left( \hat{\beta}_1^{(k-1)} + w, \hat{\beta}_2^{(k-1)} \right) + \tilde{y} \left( \hat{\beta}_1^{(k-1)} - w, \hat{\beta}_2^{(k-1)} \right) \right],
$$

(30)

Similarly to (25), we obtain $\alpha_1$ as the average of two answers with the minimum difference.

$$
\hat{\alpha}_1 = \frac{\alpha_1^{(1)} + \alpha_2^{(1)}}{2} \min_{i,j} |\alpha_1^{(i)} - \alpha_2^{(j)}|; \ i \in \{1, 2\}, \ j \in \{3, 4\}.
$$

(32)

Similarly, four answers for $\alpha_2$ can be obtained as

$$
\alpha_2^{(1/2)} = \hat{\beta}_2^{(k-1)} + \frac{1}{\kappa} \left[ \tilde{y} \left( \hat{\beta}_1^{(k-1)} + v, \hat{\beta}_2^{(k-1)} \right) + \tilde{y} \left( \hat{\beta}_1^{(k-1)} - v, \hat{\beta}_2^{(k-1)} \right) \right], \\
\alpha_2^{(1/2)} = \hat{\beta}_2^{(k-1)} + \frac{1}{\kappa} \left[ \tilde{y} \left( \hat{\beta}_1^{(k-1)} + w, \hat{\beta}_2^{(k-1)} \right) + \tilde{y} \left( \hat{\beta}_1^{(k-1)} - w, \hat{\beta}_2^{(k-1)} \right) \right],
$$

(33)

$$
\alpha_2^{(3/4)} = \hat{\beta}_2^{(k-1)} + \frac{1}{\kappa} \left[ \tilde{y} \left( \hat{\beta}_1^{(k-1)} + v, \hat{\beta}_2^{(k-1)} \right) + \tilde{y} \left( \hat{\beta}_1^{(k-1)} - v, \hat{\beta}_2^{(k-1)} \right) \right], \\
\alpha_2^{(3/4)} = \hat{\beta}_2^{(k-1)} + \frac{1}{\kappa} \left[ \tilde{y} \left( \hat{\beta}_1^{(k-1)} + w, \hat{\beta}_2^{(k-1)} \right) + \tilde{y} \left( \hat{\beta}_1^{(k-1)} - w, \hat{\beta}_2^{(k-1)} \right) \right],
$$

(34)

Then, $\hat{\alpha}_2$ can be obtained as

$$
\hat{\alpha}_2 = \frac{\alpha_2^{(1)} + \alpha_2^{(2)}}{2} \min_{i,j} |\alpha_2^{(i)} - \alpha_2^{(j)}|; \ i \in \{1, 2\}, \ j \in \{3, 4\}.
$$

(35)

Note that the parameters $\alpha_1$ and $\alpha_2$ are functions of the elevation and azimuth angles of arrival $\phi_0$ and $\theta_0$, as shown in (8) and (9). Therefore, by estimating $\alpha_1$ and $\alpha_2$, we can indirectly estimate the angles of arrival $\phi_0$ and $\theta_0$.

At the end of Algorithm 1, we can estimate the complex channel gain $h_0$ by sending one more pilot. If the BS sets $\beta_1 = \hat{\beta}_1^{(k)}$ and $\beta_2 = \hat{\beta}_2^{(k)}$, according to (5) and (16), the received signal at the BS is given by

$$
g(\beta_1, \beta_2) = h_0 \sqrt{MP_p} \times \frac{k_0 L_{\alpha}}{2} \left( \frac{a_1 - \hat{\alpha}_1^{(k)}}{\alpha_1 - \beta_1^{(k)}} \right) \times \frac{k_0 L_{\alpha}}{2} \left( \frac{a_2 - \hat{\alpha}_2^{(k)}}{\alpha_2 - \beta_2^{(k)}} \right).
$$

(37)

Then, the complex channel gain is estimated as

$$
h_0 \approx \hat{\gamma} \left( \beta_1^{(k)}, \beta_2^{(k)} \right). 
$$

(38)

**Remark 2:** The proposed algorithm involves three main operations: summation, division, and search. Specifically, based on (30), (31), and (32), the proposed scheme requires 9 summations, 5 divisions, and one search between 4 components to estimate $\alpha_1$ in each iteration. The same computation is needed to estimate $\alpha_2$. Therefore, in terms of computational complexity, the time complexity of the proposed algorithm can be expressed as $O(N)$, where $N$ is the number of iterations required for convergence.

**C. INITIAL VALUES FOR THE ITERATIVE ALGORITHM**

The performance of the proposed iterative algorithm depends on the initial values of $\beta_1^{(0)}$ and $\beta_2^{(0)}$. When the initial values of the iterative algorithm are random, the BS focuses on the reception of the pilot signals from random directions. As a result, the received signal at the BS may be comparable to the noise, which degrades the performance of the iterative algorithm. On the other hand, when the initial values are close to $\alpha_1$ and $\alpha_2$, the iterative algorithm can accurately estimate $\alpha_1$ and $\alpha_2$. In the following, we propose a simple method to provide the initial values of $\beta_1^{(0)}$ and $\beta_2^{(0)}$ that are close to $\alpha_1$ and $\alpha_2$, respectively.
In order to provide initial values, the user sends three pilot signals in three different time slots. In each time slot, the BS activates only one phase-shifting element. In the \(i\)-th time slot, the BS activates the \(A_i\)-th element, where \(A_1, A_2, \text{and } A_3\) are placed at \((0, 0), (d_r, 0), \text{and } (0, d_l)\), respectively, see Fig. 2. Let \(d_i, i \in \{1, 2, 3\}\), denote the distance between the user and the \(A_i\)-th activated element. The user sends the pilot \(x_p = \sqrt{P_p}\) to the BS, where \(P_p\) is the pilot transmit power. The received signal at the BS in the \(i\)-th time slot, denoted by \(y_i\), is given by

\[
y_1 = \frac{\sqrt{PP_\nu}}{4\pi d_0} e^{-jkod_0} + n_1, \tag{39}
\]

\[
y_2 = \frac{\sqrt{PP_\nu}}{4\pi d_0} e^{-jk_0(d_0 - d_1)} + n_2, \tag{40}
\]

\[
y_3 = \frac{\sqrt{PP_\nu}}{4\pi d_0} e^{-jk_0(d_0 - d_2)} + n_3. \tag{41}
\]

Using the phase of the received signal at the activated elements in (39)-(41), we can estimate \(a_1\) and \(a_2\) as follows

\[
\hat{a}_1 = \frac{\angle y_2 - \angle y_1}{k_0 d_r}, \tag{42}
\]

\[
\hat{a}_2 = \frac{\angle y_3 - \angle y_1}{k_0 d_r}. \tag{43}
\]

where \(\angle y_i\) denotes the phase of \(y_i\). It is worth noting that due to the noise, \(\hat{a}_1\) and \(\hat{a}_2\) are not accurate enough. Since the BS with infinitely many antennas provides super-resolution beamforming, a small error in the estimation values can degrade the performance of the system during data transmission. Therefore, these estimated values can only provide good initial values for the iterative algorithm.

**IV. EXTENSION TO NEAR-FIELD REGIME**

When the distance between the BS and the user is shorter than the Fraunhofer distance, the user lies in the near-field region of the aperture. Specifically, the near-field region of the BS is given by\(^3\)

\[
d_0 \leq \frac{2 \left( L_x^2 + L_y^2 \right)}{\lambda}. \tag{44}
\]

In conventional wireless communication systems, due to the small size of apertures and using frequencies with centimeter wavelength, the Fraunhofer distance is usually several meters, for which far-field assumption typically holds in practice. On the other hand, in future mmWave and THz communications, due to the significant increase in the electric size of apertures and operation at higher frequencies, the near-field region can be up to several hundreds of meters. For example, for an aperture of size \(L_x = L_y = 0.5\ m\) at the carrier frequency of 30 GHz, any user located at a distance of shorter than 100 m is considered to lie in the near-field region of the aperture.

\(^3\)We assume that \(d_0\) is larger than the Fresnel distance, denoted by \(d_F = \sqrt{\frac{D^2}{4\lambda}}\), so the system does not operate in the reactive near-field of the aperture \([48]\).

Similar to [43], we partition the aperture into tiles that are small enough to satisfy the far-field condition in (2). Different tiles can jointly configure their phase-shifting elements to maximize the channel through each tile to the user. As shown in Fig. 3, we assume that the aperture is partitioned into \(N_x \times N_y\) tiles of size \(L_x^{(T)} \times L_y^{(T)}\), where \(L_x^{(T)} = L_x / N_x\) and \(L_y^{(T)} = L_y / N_y\) are the width and the length of the tile, respectively. The total number of phase-shifting elements of each tile is given by \(M_x^{(T)} = M_y^{(T)} = \lambda / d_r\) and \(N_x^{(T)} = L_x^{(T)}/d_r\). Assuming \(N_x\) and \(N_y\) are odd numbers, the position of the center of the \((n_x, n_y)\)-th tile is given by \((x, y) = (n_x L_x^{(T)}, n_y L_y^{(T)})\) for \(n_x = -\frac{N_x - 1}{2}, \ldots, \frac{N_x - 1}{2}\) and \(n_y = -\frac{N_y - 1}{2}, \ldots, \frac{N_y - 1}{2}\).

We can approximately estimate the distance between the user and the aperture based on the path loss model. Let \(d_0\) denote the estimated distance between the user and the aperture. According to the far-field condition in (2), we can use the far-field channel model between a given tile of the aperture and the user if the following condition holds

\[
d_0 \geq \frac{2 \left( (L_x^{(T)})^2 + (L_y^{(T)})^2 \right)}{\lambda}, \tag{45}
\]

Substituting \(L_x^{(T)} = L_x / N_x\) and \(L_y^{(T)} = L_y / N_y\) into (45), we can obtain \(N_x\) and \(N_y\) from the following inequality

\[
d_0 \geq \frac{2 \left( \left( \frac{L_x}{N_x} \right)^2 + \left( \frac{L_y}{N_y} \right)^2 \right)}{\lambda}. \tag{46}
\]

We first focus on the channel between the \((n_x, n_y)\)-th tile of the aperture and the user. Without loss of generality, we assume that the origin of the coordinate system is placed at the center of the \((n_x, n_y)\)-th tile. Let \(\theta_{n_xn_y}\) and \(\phi_{n_xn_y}\) denote the elevation and azimuth angles of the impinging wave from the user to the center of the \((n_x, n_y)\)-th tile of the aperture. Similar to (8) and (9), let us define \(\alpha_{n_xn_y} = \sin (\theta_{n_xn_y}) \cos (\phi_{n_xn_y})\), \(\alpha_{n_xn_y} = \sin (\theta_{n_xn_y}) \sin (\phi_{n_xn_y})\), for the \((n_x, n_y)\)-th tile at the aperture. Moreover, let \(d_{n_xn_y}\) denote the distance between the center of the \((n_x, n_y)\)-th tile and the user. Assuming \(M_x^{(T)}\) and \(M_y^{(T)}\) are odd numbers, the position of the \((m_x, m_y)\)-th phase-shifting element of the \((n_x, n_y)\)-th tile is given by

**FIGURE 3.** The aperture is partitioned into tiles such that the far-field condition holds for each tile.
(x, y) = (m_xd_x, m_yd_y) for m_x = \frac{M \pi}{2}, \ldots, \frac{M \pi}{2} \text{ and } m_y = \frac{M \pi}{2}, \ldots, \frac{M \pi}{2}. \text{ Similar to Lemma 1, if we apply the following linear phase shift to the (m_x, m_y)-th phase-shifting element of the (n_x, n_y)-th tile}
\begin{align*}
\beta_{n_x n_y}^{m_x m_y} &= \mod \left( k_0 (m_x \beta_{1n_y} + m_y \beta_{2n_y}) + \beta_{0n_y} ; 2\pi \right) \\
\forall m_x, m_y,
\end{align*}

then, the channel between the (n_x, n_y)-th tile and the user, denoted by G_{n_x n_y} (\beta_{0n_x n_y}, \beta_{1n_x n_y}, \beta_{2n_x n_y}), can be obtained as
\begin{align*}
G_{n_x n_y} (\beta_{0n_x n_y}, \beta_{1n_x n_y}, \beta_{2n_x n_y}) &\approx \left( \frac{\lambda e^{-jk_0d_{n_x n_y}^T}}{4\pi d_{n_x n_y}^T} \right) \\
&\times \sqrt{F_{n_x n_y} M^T} \sin \left( \frac{k_0 L^T}{2} (\alpha_{1n_x n_y} - \beta_{1n_y}) \right) \\
&\times \sin \left( \frac{k_0 L^T}{2} (\alpha_{2n_x n_y} - \beta_{2n_y}) \right) e^{-j\beta_{0n_y} n_y},
\end{align*}

where \beta_{0n_y} determines the phase of the channel [43] and F_{n_x n_y} is the radiation power pattern of the phase-shifting elements of the (n_x, n_y)-th tile.

For ease of presentation, let us define the phase shift parameters of the aperture for all tiles as
\( (\beta_0, \beta_1, \beta_2) = \left\{ (\beta_{0n_x n_y}, \beta_{1n_x n_y}, \beta_{2n_x n_y}); \forall n_x, n_y \right\}. \) (49)
The BS-user channel in the near-field region of the BS, denoted by \( G^{(nf)}(\beta_0, \beta_1, \beta_2) \), is the superposition of the channels through individual tiles and is obtained as
\begin{align*}
G^{(nf)} (\beta_0, \beta_1, \beta_2) &\approx \sum_{n_x=0}^{N_x-1} \sum_{n_y=0}^{N_y-1} H_{n_x n_y} (\beta_{0n_x n_y}, \beta_{1n_x n_y}, \beta_{2n_x n_y}) \\
&\approx \sum_{n_x=0}^{N_x-1} \sum_{n_y=0}^{N_y-1} \left( \frac{\lambda e^{-jk_0d_{n_x n_y}^T}}{4\pi d_{n_x n_y}^T} \right) \sqrt{F_{n_x n_y} M^T} \\
&\times \sin \left( \frac{k_0 L^T}{2} (\alpha_{1n_x n_y} - \beta_{1n_y}) \right) \\
&\times \sin \left( \frac{k_0 L^T}{2} (\alpha_{2n_x n_y} \beta_{2n_y}) \right) e^{-j\beta_{0n_y} n_y}.
\end{align*}

According to (50), in order to maximize the BS-user channel in the near-field region, first, we need to maximize the channel between the (n_x, n_y)-th tile of the BS and the user in (48), i.e., \( G_{n_x n_y} (\beta_{0n_x n_y}, \beta_{1n_x n_y}, \beta_{2n_x n_y}); \forall n_x, n_y \). In order to maximize \( G_{n_x n_y} (\beta_{0n_x n_y}, \beta_{1n_x n_y}, \beta_{2n_x n_y}) \) for the (n_x, n_y)-th tile, we need to estimate two parameters, \( \alpha_{1n_x n_y} \) and \( \alpha_{2n_x n_y} \). Finally, \( \beta_{0n_x n_y}, \forall n_x, n_y \) in (50) can be obtained such that the channels through the individual tiles have the same phase.

Since the number of tiles is \( N_x \times N_y \), we need to estimate \( 2N_x \times N_y \) parameters for the near-field region of the BS. Note that these parameters depend on each other, and we use this dependency in the proposed channel estimation scheme.

In fact, by partitioning the aperture into tiles in the near-field, the signal wavefront can be seen as a plane wave for each tile. Although the elevation and azimuth angles of these impinging plane waves from the user to the tiles are different, the difference between the unknown parameters \( (\alpha_{1n_x n_y}, \alpha_{2n_x n_y}) \) for neighboring tiles is small. Following the above example, for an aperture of size \( L_x = L_y = 0.5 \text{ m} \) at carrier frequency of 30 GHz, assume that the distance between the user and the center of the aperture is \( d_0 = 30 \text{ m} \) and the elevation and azimuth angles are \( \theta = 30^\circ \) and \( \phi = 60^\circ \). Since the user lies in the near-field region of the aperture, we partition the aperture into four tiles of size \( 0.25 \text{ m} \times 0.25 \text{ m} \) where the far-field distance for each tile becomes \( d_0 = 25 \text{ m} \) and far-field assumption holds. Then, the unknown parameters \( (\alpha_1, \alpha_2) \), for these tiles are \( (0.253, 0.436), (0.254, 0.429), (0.246, 0.437), \) and \( (0.247, 0.430) \). We exploit the proximity between these unknown parameters in the proposed channel estimation scheme for near-field to reduce the estimation overhead.

For the near-field region, we use (42) and (43) to provide initial values for the iterative algorithm. Then, we apply Algorithm 1 to the tile close at the center of the aperture to estimate the unknown parameters of the tile \( (\alpha_1, \alpha_2) \). For each of the remaining tiles, since each tile’s unknown parameters are very close to its neighbouring tiles’ parameters, we consider the average of estimated values of the neighbouring tiles as the initial values. Then, we apply Algorithm 1 to estimate the unknown parameters of each tile. Due to good initial values, the number of iterations in Algorithm 1 decreases, and hence the overhead of the proposed scheme will be reduced.

After estimating the unknown parameters of the tiles, we send one more pilot for each tile to obtain the phase of the channel between each tile and the user. Finally, we use (47) to configure the phase-shifting elements of all tiles, in which \( \beta_{0n_y} \) is the phase of the channel between \( (n_x, n_y)-\text{th tile} \) and the user.

**Remark 3:** In the channel estimation scheme based on the location of the user, three parameters are needed to be estimated, i.e., \( d_0, \alpha_1, \) and \( \alpha_2 \). Compared to these schemes, partitioning the aperture to the tiles increases the number of unknown parameters from three to \( 2N_x \times N_y \). However, the beam created by the entire aperture has a narrower beamwidth compared to each tile. Therefore, an error in the estimation of the location potentially has a more significant negative impact on the performance of the location-based schemes, especially for large apertures. In other words, in the location-based schemes, an error in the location estimation causes an error in the configuration of all phase-shifting elements. In contrast, an error in the estimation of \( \alpha_{1n_x n_y} \) and \( \alpha_{2n_x n_y} \) only cause an error in the configuration of that tile, not the entire aperture. In addition, it is clear from (50) that the idea of partitioning ensures constructive superposition by \( \beta_{0n_y} \).
**TABLE 1. A list of system parameters for numerical experiments.**

| Symbol | Value | Description |
|--------|-------|-------------|
| \( f_c \) | 30 GHz | Carrier frequency |
| \( \lambda \) | 1 cm | Wavelength |
| \( M_x \) | 257 | Number of antennas along x axis |
| \( M_y \) | 257 | Number of antennas along y axis |
| \( d_r \) | \( \lambda/4 \) | Unit element spacing |
| \( L_e \) | 0.8 \( d_r \) | Width and length of each phase-shifting element |
| \( d_0 \) | 180(10)m | BS-user distance for far-field (near-field) region |
| \( P_t \) | 30 dBm | Transmit power of the BS during data transmission |
| \( N_0 \) | 6.95 dBm | Noise power for 20 MHz |
| \( Q \) | 4 | Number of NLoS paths |

**V. NUMERICAL RESULTS**

In this section, we provide the numerical results to evaluate the performance of the proposed channel estimation algorithm.

**A. SETTINGS OF THE NUMERICAL EXPERIMENTS**

In this subsection, we explain the parameter setup of the numerical experiments. The simulation results have been averaged over 1000 random channel realization. In each channel realization, while the distance between the user and the center of the BS is fixed, the elevation and azimuth angles of the LoS path follow the uniform distribution, i.e., \( \theta \sim U(0, \pi/2) \), \( \phi \sim U(0, 2\pi) \). We consider the uniform distribution of the angles as the worst-case scenario. However, as shown in [52], there are circumstances when the angles have non-uniform distribution. In addition to the LoS path, we assume that there are 4 NLoS paths due to scatters between the user and the BS. The elevation and azimuth angles of each NLoS path from those scatters to the center of aperture follow the uniform distribution. Moreover, we model the path coefficient of each NLoS path as a complex Gaussian random variable, i.e., \( CN(0, \sigma^2) \), where \( \sigma^2 \) is 20 dB weaker than the power of the LoS component [47]. To evaluate the performance of the proposed scheme in both far-field and near-field regions, we consider the distance between the user and the BS, \( d_0 \), as 180m for the far-field region and 10m for the near-field region. Unless otherwise specified, the system parameters for numerical experiments are listed in Table 1.

**B. PERFORMANCE EVALUATION**

In this section, we present the numerical results for the proposed algorithm and make comparisons with other channel estimation schemes. Three benchmark schemes are considered for comparison, including a hierarchical search scheme, a CS-based channel estimation scheme, and localization-based channel estimation.

**Benchmark Scheme 1:** In the hierarchical search scheme, proposed in [20], closed-form expressions are provided to generate a codebook consisting of codewords with different beam widths. In this scheme, joint sub-array and deactivation approach is exploited to design a binary-tree codebook. The codebook consists of \([\log_2 M]+1 \) layers with indices from \( k = 0 \) to \( k = \log_2 M \) and the number of codewords in each layer is \( 2^k \). The beam width of the codewords in the \( k \)-th layer is \( \frac{\lambda}{2^k} \). In addition, codewords in the same layer have the same beam widths but different steering angles. Therefore, there are two basic tasks in the codebook design, namely to rotate the beam along required directions and to broaden the beam by required factors. The pilot overhead of this hierarchical scheme is given by \( 2 \log_2 (M) \), where \( M \) is the number of phase-shifting elements at the aperture [20].

**Benchmark Scheme 2:** In the CS-based channel estimation scheme, proposed in [25], the problem is formulated as a sparse signal recovery problem. Then, the problem is solved by the orthogonal matching pursuit algorithm employing non-uniformly quantized angle grids. To be more specific, the BS sweeps \( M \) unit-norm training beams to measure the channel. Then, we use the virtual angular domain representation to provide a discrete approximation of the physical channel. Finally, we use OMP to solve the single measurement vector (SMV)-based problem. The pilot overhead of this scheme is given by \( O((Q+1) \ln (M)) \), where \( Q \) is the number of NLoS channels [25].

**Benchmark Scheme 3:** In the near-field of the BS, the channel is characterized by the location of the user. Therefore, we consider a localization scheme to estimate the channel by the location parameters. Work [42] uses the maximum likelihood estimator to estimate the position of the user in the near-field of a uniform planar array. The approach involves modeling the received signal as a sum of complex exponentials, where each exponential corresponds to a path between the transmitter and an element in the array. The parameters of the model include the amplitudes and phases of the complex exponentials, as well as the position of the user. The maximum likelihood estimator seeks to find the values of these parameters that maximize the likelihood of observing the measured channel data.

The BS uses the acquired CSI during the channel estimation period to maximize the received data rate by the user. Therefore, we consider the achieved data rate by the user using the acquired CSI as a performance metric. The achieved data rate is calculated by

\[
R = \log_2 \left( 1 + \frac{P_t |\text{vec} \left( \Gamma \right) \text{vec} \left( H \right) |^2}{N_0} \right). \tag{51}
\]

where \( N_0 \) represents the AWGN power, \( P_t \) is the transmission power at the BS, \( \text{vec} \left( \Gamma \right) \text{vec} \left( H \right) \) refers to channel between the BS and the user. Specifically, \( \Gamma \) is the beamforming weight matrix in (10) and \( H \) is the channel between the user and the aperture, as given in (3). It is worthwhile to note that the imperfect CSI is used for the configuration of the elements of the aperture, whereas a high quality CSI of the scalar end-to-end channel (including beamforming at the transmitter) will be acquired at the user with almost perfect phase estimation to enable coherent communication.
Fig. 4 illustrates the achieved data rate of the proposed scheme and the benchmark schemes as a function of the transmission power of the pilot signals. In addition, in this figure, we compare the performance of the proposed scheme with the benchmark schemes in both the far-field and near-field regions of the BS. In the far-field region of the BS, we set the maximum number of iteration of the proposed scheme to 4. For the near-field, we partitioned the aperture into 4 tiles. For each tile, we set the number of iteration to one. Since each iteration requires five pilot signals and three pilot signals are required to provide the initial values, the maximum total number of pilot signals is 23. It can be observed from Fig. 4 that when the power of the pilot signals is low, the noise is comparable to the received pilot signals, and hence the proposed scheme cannot estimate the unknown parameters accurately. However, when the power of the pilot signal increases, the received pilot signals are much stronger than the noise, and hence the estimation error decreases.

As illustrated in Fig. 4, the proposed scheme, in general, achieves a significant gain over the other benchmark schemes since it exploits the specific structure of the radiated beam (the sinc function) in the LoS dominated channel model.

In Fig. 5, we show the achieved data rate of the proposed scheme and the benchmark schemes as a function of the number of pilot signals. In this figure, we fix the transmit power of the pilot signals to 20 dBm. We observe from Fig. 5 that the achieved data rate of the proposed and benchmark schemes increases with the number of pilot signals. In the far-field region of the BS, the proposed, hierarchical, and CS schemes can approximately achieve the maximum rate when the number of pilot signals is more than 30. In the near-field region of the BS, the achieved data rate of the CS scheme
cannot increase more than a certain value due to the assumption of quantized values for $\alpha_1$ and $\alpha_2$. It can be observed from Fig. 5 that the proposed scheme outperforms all benchmark schemes for the different number of pilot signals.

Fig. 6 compares the achieved data rate by the proposed scheme with the benchmark schemes for two different numbers of phase-shifting elements at the aperture. Similar to Fig. 4, the number of pilot signals is fixed to 23. Assuming perfect CSI, the achieved data rate has to increase with $M$. Nevertheless, the performance of the hierarchical scheme does not change with $M$. This is due to the fact that when $M$ increases, the signal beam width is narrower, and hence, more accurate estimations for $\alpha_1$ and $\alpha_2$ are required, which is not feasible with a low number of pilot signals. In addition, the performance of the CS scheme decreases as the pilot overhead of the CS scheme increases, which is $O((Q + 1) \ln (M))$. On the other hand, the achieved data rate of the proposed scheme increases with $M$ since accurate estimation for $\alpha_1$ and $\alpha_2$ can be obtained by the proposed scheme.

Fig. 7 illustrates the achieved data rate of the proposed scheme and the benchmark schemes as a function of the power difference of LoS and NLoS paths. The horizontal axis of this figure indicates that how much the power of NLoS path components is weaker than the power of the LoS component. In this figure, the transmit power and the number of the pilot signals are fixed to 20 dBm and 23, respectively. In the proposed scheme, we consider the effect of NLoS path components as interference. As a result, when the power of NLoS path components decreases, the proposed scheme can estimate $\alpha_1$ and $\alpha_2$ more accurately. As shown in Fig. 7, the proposed scheme outperforms all benchmark schemes even when the power of NLoS path components is comparable to the power of LoS path component.

In Fig. 8, we compare the convergence behavior of the proposed scheme with the hierarchical and localization schemes. We consider the mean square error (MSE) to study the convergence behaviour, which is defined by $\text{MSE}_i = \mathbb{E}(|\alpha_i - \hat{\alpha}_i|^2), \forall i \in \{1, 2\}$. In this figure, we fix the transmit power and the distance between the BS and the user to 20 dBm and 25 m, respectively. Since the CS scheme estimates the whole channel, not the AoA/AoD, we compare the proposed scheme only with the hierarchical and localization schemes. We observe from Fig. 8 that when the number of pilot signals increases, the MSE of the proposed scheme and the benchmark schemes decreases. In the hierarchical scheme, when the number of pilot signals increases, narrower beam widths are used to estimate $\alpha_1$ and $\alpha_2$ more accurately. However, since $M_1 = M_2 = 257$, after $[\log_2 257] = 8$ iteration, the MSE of the hierarchical scheme does not decrease. Fig. 8 suggests that the proposed scheme and localization scheme can accurately estimate $\alpha_1$ and $\alpha_2$ when the number of pilot signals is more than 23 (4 iterations in Algorithm 1).

In Fig. 9, we show the number of pilot signals required to achieve the desired MSE = $10^{-6}$ vs. the transmit power of the pilot signals when the distance between the BS and the user are fixed to 25 m. In this figure, we fix the transmit power and the distance between the BS and the user to 10 $^{-6}$ and 25 m, respectively. We observe from Fig. 9 that the required number of pilot signals of the proposed and benchmark schemes decreases with the transmission power of the pilot signals. In addition, when the transmission power of the pilot signals is more than $-5 \text{ dBm}$, the proposed scheme needs less number of pilot signals compared to the benchmark scheme to achieve the MSE = $10^{-6}$. Fig. 9 suggests that at a high signal to noise ratio (SNR) regime, the proposed scheme requires only five pilots to perfectly estimate the unknown channel parameters. This is because the proposed scheme exploits the specific structure of the radiated beams (two sinc functions) to estimate the unknown parameters.

VI. CONCLUSION

In this paper, we proposed a channel estimation scheme for the holographic massive MIMO systems in the dominated LoS channel model. In the far-field region, we modeled the
channel based on the path parameters of the system. We show that only two path parameters are required to be estimated to obtain the optimal phase shifts for all phase-shifting elements of the aperture. For the near-field, we first partitioned the aperture into tiles. Then, the channel was modeled as the superposition of the channels through the individual tiles. Moreover, only two parameters are required to be estimated for each tile. The proposed channel estimation scheme exploits the specific structure of the radiated beams (two sinc functions) to estimate the unknown parameters. The simulation results verified that the proposed scheme achieves significant performance gains over existing channel estimation schemes.

**APPENDIX**

### A. PROOF OF LEMMA 1

We start the proof by substituting the linear phase shift in (12) into (11). We have

$$G(\beta) \approx \left( \frac{\sqrt{F}e^{-jkd_0}}{4\pi d_0} \right) \sum_{m=-M_1}^{M_1-1} e^{jkd_0} \left( m_1(\alpha_1 - \beta_1) \right)$$

Using the terms of a geometric progression, we can write

$$\sum_{m=-M_1}^{M_1-1} e^{jma} = \frac{e^{j(M_1-1)a} \left( 1 - e^{Ja} \right)}{1 - e^{Ja}} = \sin\left( \frac{Ma}{2} \right) \sin\left( \frac{a}{2} \right).$$

Now, using (53) in (52), we have

$$G(\beta) \approx \left( \frac{\sqrt{F}e^{-jkd_0}}{4\pi d_0} \right) \sin\left( \frac{M_2kd_0}{2} \right) \left( \alpha_1 - \beta_1 \right)$$

$$\times \sin\left( \frac{M_2kd_0}{2} \right) \left( \alpha_2 - \beta_2 \right).$$

Substituting $M_x = L_x/d_x$ and $M_y = L_y/d_y$ into (14) completes the proof.

**REFERENCES**

[1] C. Chaccour, M. N. Soorki, W. Saad, M. Bernis, P. Popovski, and M. Debbah, “Seven defining features of terahertz (THz) wireless systems: A fellowship of communication and sensing,” IEEE Commun. Surveys Tuts., vol. 24, no. 2, pp. 967–993, 2nd Quart., 2022.

[2] W. Tang, X. Chen, M. Z. Chen, J. Y. Dai, Y. Han, M. D. Renzo, S. Jin, Q. Cheng, and T. J. Cui, “Path loss modeling and measurements for reconfigurable intelligent surfaces in the millimeter-wave frequency band,” IEEE Trans. Commun., vol. 70, no. 9, pp. 6259–6276, Sep. 2022.

[3] Z. Wan, Z. Gao, F. Gao, M. Di Renzo, and M.-S. Alouini, “Terahertz massive MIMO with holographic reconfigurable intelligent surfaces,” IEEE Trans. Commun., vol. 69, no. 7, pp. 4732–4750, Jul. 2021.

[4] V. Jamali, A. M. Tulino, G. Fischer, R. R. Müller, and R. Schober, “Intelligent surface-aided transmitter architectures for millimeter-wave ultra massive MIMO systems,” IEEE Open J. Commun. Soc., vol. 2, pp. 144–167, 2021.

[5] L. Wei, R. Q. Hu, Y. Qian, and G. Wu, “Key elements to enable millimeter wave communications for 5G wireless systems,” IEEE Wireless Commun., vol. 21, no. 6, pp. 136–143, Dec. 2014.

[6] E. G. Larsson, O. Edfors, F. Tufvesson, and T. L. Marzetta, “Massive MIMO for next generation wireless systems,” IEEE Commun. Mag., vol. 52, no. 2, pp. 186–195, Feb. 2014.

[7] Y. Zhu, G. Zheng, and K.-K. Wong, “Stochastic geometry analysis of large intelligent surface-assisted millimeter wave networks,” IEEE J. Sel. Areas Commun., vol. 38, no. 8, pp. 1749–1762, Aug. 2020.

[8] E. Heinron, L. Sanguinetti, H. Wymeersch, J. Hoydis, and T. L. Marzetta, “Massive MIMO is a reality—What is next? Five promising research directions for antenna arrays,” Digit. Signal Process., vol. 94, pp. 3–20, Nov. 2019.

[9] D. Dardari, “Communicating with large intelligent surfaces: Fundamental limits and models,” IEEE J. Sel. Areas Commun., vol. 38, no. 11, pp. 2526–2537, Nov. 2020.

[10] S. Noh, M. D. Zoltowski, and D. J. Love, “Multi-resolution codebook for millimeter wave massive MIMO,” IEEE Commun. Mag., vol. 57, no. 11, pp. 106–113, Apr. 2021.

[11] M. Di Renzo, A. Zappone, M. Debbah, M. S. Alouini, C. Yuen, J. De Rosny, and S. Tret’yakov, “Smart radio environments empowered by reconfigurable intelligent surfaces: How it works, state of research, and the road ahead,” IEEE J. Sel. Areas Commun., vol. 38, no. 11, pp. 2450–2525, Jul. 2020.

[12] Q. Wu, S. Zhang, B. Zheng, C. You, and R. Zhang, “Intelligent reflecting surface aided wireless communications: A tutorial,” IEEE Trans. Commmun., vol. 69, no. 5, pp. 3313–3351, May 2021.

[13] Q. Wu and R. Zhang, “Intelligent reflecting surface enhanced wireless network via joint active and passive beamforming,” IEEE Trans. Wireless Commun., vol. 18, no. 11, pp. 5394–5409, Nov. 2019.

[14] M. Jung, W. Saad, and G. Kong, “Performance analysis of active large intelligent surfaces (LiSs): Uplink spectral efficiency and pilot training,” IEEE Trans. Commun., vol. 69, no. 5, pp. 3379–3394, May 2021.

[15] S. Hu, F. Rusek, and O. Edfors, “Beyond massive MIMO: The potential of data transmission with large intelligent surfaces,” IEEE Trans. Signal Process., vol. 66, no. 10, pp. 2746–2758, May 2018.

[16] J. Yuan, H. Q. Ngo, and M. Matthaiou, “Towards large intelligent surface (LiS)-based communications,” IEEE Trans. Commun., vol. 68, no. 10, pp. 6568–6582, Oct. 2020.

[17] S. Hu, F. Rusek, and O. Edfors, “Beyond massive MIMO: The potential of data transmission with large intelligent surfaces,” IEEE Trans. Signal Process., vol. 64, no. 7, pp. 1761–1774, Apr. 2018.

[18] F. Dai and J. Wu, “Efficient broadcasting in ad hoc wireless networks using directional antennas,” IEEE Trans. Parallel Distrib. Syst., vol. 17, no. 4, pp. 335–347, Apr. 2006.

[19] Z. Xiao, T. He, P. Xia, and X.-G. Xia, “Hierarchical codebook design for beamforming training in millimeter-wave communication,” IEEE Trans. Wireless Commun., vol. 15, no. 5, pp. 3380–3392, May 2016.

[20] Z. Zhang, Y. Huang, Q. Shi, J. Wang, and L. Yang, “Codebook design for beam alignment in millimeter wave communication systems,” IEEE Commun. Mag., vol. 52, no. 2, pp. 186–195, Feb. 2014.

[21] M. Jung, W. Saad, and G. Kong, “Performance analysis of active large intelligent surfaces (LiSs): Uplink spectral efficiency and pilot training,” IEEE Trans. Commun., vol. 69, no. 5, pp. 3379–3394, May 2021.

[22] J. Yuan, H. Q. Ngo, and M. Matthaiou, “Towards large intelligent surface (LiS)-based communications,” IEEE Trans. Commun., vol. 68, no. 10, pp. 6568–6582, Oct. 2020.

[23] S. Hu, F. Rusek, and O. Edfors, “Beyond massive MIMO: The potential of data transmission with large intelligent surfaces,” IEEE Trans. Signal Process., vol. 66, no. 10, pp. 2746–2758, May 2018.

[24] J. Zhang, Y. Huang, Q. Shi, J. Wang, and L. Yang, “Codebook design for beam alignment in millimeter wave communication systems,” IEEE Commun. Mag., vol. 65, no. 11, pp. 4980–4995, Nov. 2017.

[25] D. Noh, M. D. Zoltowski, and D. J. Love, “Multi-resolution codebook and adaptive beamforming sequence design for millimeter wave beam alignment,” IEEE Trans. Wireless Commun., vol. 16, no. 9, pp. 5689–5701, Sep. 2017.

[26] C.-R. Tsai, Y.-H. Liu, and A.-Y. Wu, “Efficient compressive channel estimation for millimeter-wave large-scale antenna systems,” IEEE Trans. Signal Process., vol. 66, no. 9, pp. 2414–2428, May 2018.
[26] X. Ma, F. Yang, S. Liu, J. Song, and Z. Han, “Design and optimization on training sequence for mmWave communications: A new approach for sparse channel estimation in massive MIMO,” IEEE J. Sel. Areas Commun., vol. 35, no. 7, pp. 1486–1497, Jul. 2017.

[27] Y. Peng, Y. Li, and P. Wang, “An enhanced channel estimation method for millimeter wave systems with massive antenna arrays,” IEEE Commun. Lett., vol. 19, no. 9, pp. 1592–1595, Sep. 2015.

[28] S. H. Lim, S. Kim, B. Shim, and J. W. Choi, “Efficient beam training and sparse channel estimation for millimeter wave communications under mobility,” IEEE Trans. Commun., vol. 68, no. 10, pp. 6583–6596, Oct. 2020.

[29] Z. Gao, L. Dai, Z. Wang, and S. Chen, “Spatially common sparsity based adaptive channel estimation and feedback for FDD massive MIMO,” IEEE Trans. Signal Process., vol. 63, no. 23, pp. 6169–6183, Dec. 2015.

[30] S. Pejoski and V. Kafezdivski, “Estimation of sparse time dispersive channels in pilot aided OFDM using atomic norm,” IEEE Wireless Commun. Lett., vol. 4, no. 4, pp. 397–400, Aug. 2015.

[31] H. Chu, L. Zheng, and X. Wang, “Super-resolution mmWave channel estimation for generalized spatial modulation systems,” IEEE J. Sel. Topics Signal Process., vol. 13, no. 6, pp. 1336–1347, Oct. 2019.

[32] M. Sanchez-Fernandez, V. Jamali, J. Llorca, and A. M. Tulino, “Gridless multidimensional angle-of-arrival estimation for arbitrary 3D antenna arrays,” IEEE Trans. Wireless Commun., vol. 20, no. 7, pp. 4748–4764, Jul. 2021.

[33] R. Shafin, L. Liu, Y. Li, A. Wang, and J. Zhang, “Angle and delay estimation for 3-D massive MIMO/FD-MIMO systems based on parametric channel modeling,” IEEE Trans. Wireless Commun., vol. 16, no. 8, pp. 5370–5383, Aug. 2017.

[34] J. He, H. Wyneersch, and M. Junnti, “Channel estimation for RIS-aided mmWave MIMO systems via atomic norm minimization,” IEEE Trans. Wireless Commun., vol. 20, no. 9, pp. 5786–5797, Sep. 2021.

[35] K. Li, M. El-Hajjar, and L.-L. Yang, “Millimeter-wave based localization using a two-stage channel estimation relying on few-bit ADCs,” IEEE Open J. Commun. Soc., vol. 2, pp. 1736–1752, 2021.

[36] Y. Wang and K. C. Ho, “Unified near-field and far-field localization for AOA and hybrid AOA-TDOA positionings,” IEEE Trans. Wireless Commun., vol. 17, no. 2, pp. 1242–1254, Feb. 2018.

[37] H. Wyneersch, I. He, B. Denis, A. Clemente, and M. Junnti, “Radio localization and mapping with reconfigurable intelligent surfaces: Challenges, opportunities, and research directions,” IEEE Veh. Technol. Mag., vol. 15, no. 4, pp. 52–61, Dec. 2020.

[38] A. Shahmansoori, G. E. Garcia, G. Destino, G. Seco-Granados, and H. Wyneersch, “Position and orientation estimation through millimeter-wave MIMO in 5G systems,” IEEE Trans. Wireless Commun., vol. 17, no. 3, pp. 1822–1835, Mar. 2018.

[39] H. Zhang, H. Zhang, B. Di, K. Bian, Z. Han, and L. Song, “Metadata localization: Reconfigurable intelligent surface aided multi-user wireless indoor localization,” IEEE Trans. Wireless Commun., vol. 20, no. 12, pp. 7743–7757, Dec. 2021.

[40] X. Li, E. Leitinger, M. Oskarsson, K. Åström, and F. Tufvesson, “Massive MIMO-based localization and mapping exploiting phase information of multipath components,” IEEE Trans. Wireless Commun., vol. 18, no. 9, pp. 4234–4267, Sep. 2019.

[41] R. Mendzrik, H. Wyneersch, G. Bauch, and Z. Abu-Shaban, “Harnessing NLOS components for position and orientation estimation in 5G millimeter wave MIMO,” IEEE Trans. Wireless Commun., vol. 18, no. 1, pp. 93–107, Jan. 2019.

[42] F. Guidi and D. Dardari, “Radio positioning with EM processing of the spherical wavefront,” IEEE Trans. Wireless Commun., vol. 20, no. 6, pp. 3571–3586, Jun. 2021.

[43] M. Najafi, V. Jamali, R. Schober, and H. V. Poor, “Physics-based modeling and scalable optimization of large intelligent reflecting surfaces,” IEEE Trans. Commun., vol. 69, no. 4, pp. 2673–2691, Apr. 2021.

[44] S. W. Ellingson, “Path loss in reconfigurable intelligent surface-enabled channels,” in Proc. IEEE 32nd Annu. Int. Symp. Pers., Indoor Mobile Radio Commun. (PIMRC), Sep. 2021, pp. 829–835.

[45] M. R. Akdeniz, Y. Liu, M. K. Samimi, S. Sun, S. Rangan, T. S. Rappaport, and E. Erkip, “Millimeter wave channel modeling and cellular capacity evaluation,” IEEE J. Sel. Areas Commun., vol. 32, no. 6, pp. 1164–1179, Apr. 2014.

[46] Z. Muhii-Eldeen, L. P. Ivrisissentzis, and M. Al-Nuaimi, “Modelling and measurements of millimetre wavelength propagation in urban environments,” IET Microw., Antennas Propag., vol. 4, no. 9, pp. 1300–1309, Sep. 2010.

[47] W. Wang and W. Zhang, “Joint beam training and positioning for intelligent reflecting surfaces assisted millimeter wave communications,” IEEE Trans. Wireless Commun., vol. 20, no. 10, pp. 6282–6297, Oct. 2021.

[48] C. A. Balanis, Antenna Theory: Analysis and Design. Hoboken, NJ, USA: Wiley, 2016.

[49] K. T. Selvan and R. Janaswamy, “Fraunhofer and Fresnel distances: Unified derivation for aperture antennas,” IEEE Antennas Propag. Mag., vol. 39, no. 4, pp. 12–15, Aug. 2017.

[50] I. S. Gradshteyn and I. M. Ryzhik, Table of Integrals, Series, and Products. San Diego, CA, USA: Academic Press, 1994.

[51] Z. Wang, L. Liu, and S. Cui, “Channel estimation for intelligent reflecting surface assisted multiuser communications: Framework, algorithms, and analysis,” IEEE Trans. Wireless Commun., vol. 19, no. 10, pp. 6607–6620, Jun. 2020.

[52] W. Tan and S. Ma, “Antenna array topologies for mmWave massive MIMO systems: Spectral efficiency analysis,” IEEE Trans. Veh. Technol., vol. 71, no. 12, pp. 12901–12915, Dec. 2022.

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