A Survey on Near-Field Communication Systems : Channel Estimation, Beam Alignment, CSI Feedback

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***Abstract*—Extremely large-scale antenna array (ELAA) is key enabler of stringent requirement for sixth generation (6G) mobile networks, such as ultra-high data rate, and terahertz communications. Due to the extremely large number of antennas in ELAA, the impinging wavefront must be characterized by spherical waves, which deviates from the conventional planar-wave assumption in massive MIMO. As a result, near-field MIMO communications cannot be neglected in 6G wireless networks. In this paper, we comprehensively investigate the near-field communication techniques. First, we present the fundamentals of near-field communications and the metric to determine the near-field ranges in typical communication scenarios. Then we investigate recent works in near-field communications, classifying them into three categories: channel estimation, beam training, and CSI feedback schemes developed to address spherical wave-front effects.**

***Index Terms*—Massive MIMO, Channel Estimation, Beam Training, CSI Feedback, 6G, Terahertz Communication**

I. Introduction

Massive MIMO provides substantial spectral and energy efficiency by simultaneously serving multiple users with massive amount of antennas, while also enabling effective interference suppression through spatial precoding [1]. These benefits establish massive MIMO as a cornerstone technology in wireless communications up to the present generation. Although, to meet the extreme performance requirements of sixth-generation (6G) wireless communication systems such as Tbps-level data rates, and ultra-reliable low-latency communications, the conventional massive MIMO architecture must undergo substantial enhancements [2]–[4]. Considering this situation, extremely large-scale antenna arrays (ELAAs) are needed, providing higher spatial resolution, stronger array gain. Specifically, deploying terahertz (THz) bands results in significant path loss and restricted coverage, making traditional massive MIMO inadequate. In contrast, ELAA systems, comprising hundreds to thousands of antennas, provide highly precise beam-focusing capabilities, thereby effectively mitigating the substantial path loss associated with the THz range [5].

In ELAA systems, the aperture of the antenna array becomes comparable to or even larger than the Rayleigh distance, defined as $2D^2/\lambda$ where D and λ represents the size of array aperture and wavelength. When users are located within this distance, the impinging signals can no longer be approximated as planar waves, as assumed in massive MIMO. Instead, the wavefronts become spherical, with received phase across antennas influenced by both angle of arrival and propagation distance. This transition introduces angle–range dependent channels, fundamentally change the ELAA-enabled 6G systems [6].

We investigate recent works in near-field communication systems classifying them into three categories: channel estimation, beam training, and CSI feedback schemes developed to address spherical wavefront effects [7]–[9]. This categorization is motivated by the fact that accurate channel estimation is indispensable for acquiring angle–range dependent channel parameters, beam training ensures effective beam alignment under spherical wavefront propagation, and CSI feedback enables efficient transmission of channel information back to the base station. While each aspect addresses a distinct problem, they are inherently interconnected, as the basis for constructing effective codebook is essential to accurate channel estimation, beam training, and CSI feedback requires compact representations of the same codebooks for efficient reporting.

II. Foundations of Near-Field Communications

A. *Bounadaries for Communication Regions*

Conventionally, the propagation characteristics of RF waves can be categorized into three distinct regions based on the radiation distance: the reactive near-field, the radiative near-field,and the far-field [10]. The reactive near-field region is the closest area surrounding an antenna, where the electric and magnetic fields are strongly coupled and predominantly non-radiative. This region extends up to approximately $0.62\sqrt{D^3/\lambda}$. In this regime, electromagnetic energy is largely stored rather than radiated, and the field distribution is highly non-uniform. Due to these properties, the effective communication distance in the reactive near-field is extremely limited, and accurate channel modeling becomes impractical. As a result, this region is generally not considered in near-field communication studies.

By contrast, the radiative near-field region (or Fresnel region) extends beyond the reactive near-field and up to the Rayleigh distance, typically defined as $0.62\sqrt{D^3/\lambda} < r < 2D^2/\lambda$. In this regime, the impinging wavefronts become spherical rather than planar, and both angle and distance jointly determine the received phase across antenna elements. These properties make the radiative near-field particularly relevant for 6G ELAA and THz systems, enabling advanced beam focusing, localization, and integrated sensing and communication.

The far-field region, or Fraunhofer region, is defined for distances greater than $2D^2/\lambda$. In this regime, wavefronts are well approximated by plane waves, and the electric and magnetic fields form a uniform transverse electromagnetic wave orthogonal to the propagation direction. The radiation pattern of the antenna becomes distance-independent, making this regime the foundation for most conventional wireless systems. Accordingly, far-field models underlie the design of traditional beamforming, channel estimation, and antenna measurements in existing communication standards such as 4G, 5G massive MIMO, and satellite communications.

B. Far-field and Near-field MIMO Channel Models

In this subsection, we describe the far-field and near-field channel model under uniform linear array (ULA). When the user is located beyond the Rayleigh distance, the arriving signals can be accurately modeled by the planar-wave assumption, and the array response depends only on the angle of arrival/departure (AoA/AoD). The array steering vector for an N-element uniform linear array (ULA) is given by

$$\mathbf{a}_{\text{FF}}(\theta) = \sqrt{\frac{1}{N}} \left[1,\ e^{-j\frac{2\pi d}{\lambda}\theta},\ \ldots,\ e^{-j\frac{2\pi d}{\lambda}(N-1)\theta}\right]^T, \quad (1)$$

where N, d, and $-1 \leq \theta \leq 1$ are the number of antenna, antenna spacing and spatial angle. Accordingly, the channel vector under L multipath components can be expressed as

$$\mathbf{h}_{\text{FF}} = \sum_{\ell=1}^{L} \alpha_\ell\, \mathbf{a}_{\text{FF}}(\theta_\ell), \quad (2)$$

where α_ℓ and θ_l denote the complex path gain and spatial angle of the ℓ-th path. This model leads to *angular-domain sparsity*, since the channel can be well represented by a small number of dominant angles corresponding to the limited scattering paths. In particular, the far-field array steering vectors are well represented the columns of a discrete Fourier transform (DFT) matrix $\mathbf{U} \in \mathbb{C}^{N\times N}$, which allows the channel to be expressed in the beamspace domain as

$$\tilde{\mathbf{h}}_{\text{FF}} = \mathbf{U}^H \mathbf{h}_{\text{FF}}, \quad (3)$$

where $\tilde{\mathbf{h}}_{\text{FF}}$ denotes its beamspace channel vector. Due to the angular sparsity, only a few entries of $\tilde{\mathbf{h}}_{\text{FF}}$ corresponding to the dominant angle bins carry significant power, while the rest are nearly negligible. This property justifies the widespread use of DFT-based beamspace channel representations in far-field massive MIMO systems.

In contrast, when the user located in the radiative region, the planar-wave approximation is no longer valid, and the channel must be characterized by spherical wavefronts, which implies that the propagation distance between the BS and the UE becomes a critical parameter. The propagation distance between the n-th antenna and a user is given by

$$r^{(n)} = \sqrt{r^2 + (nd)^2 - 2rnd\theta}, \quad (4)$$

where r is a distance between center of antenna array and user [7]. The near-field array steering vector becomes

$$\mathbf{a}_{\text{NF}}(r,\theta) = \frac{1}{\sqrt{N}} \left[e^{-j\frac{2\pi}{\lambda}r^{(0)}}, e^{-j\frac{2\pi}{\lambda}r^{(1)}},\ \ldots,\ e^{-j\frac{2\pi}{\lambda}r^{(N-1)}}\right]^T, \quad (5)$$

and the channel vector under L multipath components can be expressed as

$$\mathbf{h}_{\text{NF}} = \sum_{\ell=1}^{L} \alpha_\ell\, \mathbf{a}_{\text{NF}}(r_\ell,\theta_\ell). \quad (6)$$

where r_l and θ_l means the propagation distance and spatial angle of the ℓ-th path. This model exhibits *angle–distance domain sparsity*, which fundamentally differs from the angular-only sparsity of the far-field case and introduces new challenges for channel estimation, beam training, and CSI feedback. Mathematically, the near-field channel can be represented as

$$\tilde{\mathbf{h}}_{\text{NF}} = \mathbf{\Psi}^H \mathbf{h}_{\text{NF}}, \quad (7)$$

where $\mathbf{\Psi} \in \mathbb{C}^{N\times S}$ denotes a polar-domain dictionary constructed over angle-distance grids. Such a representation directly motivates the design of near-field codebook enabling precise beam focusing and efficient CSI acquisition. The differences between the far-field and near-field channel models are summarized in Table I.

TABLE I
COMPARISON BETWEEN FAR-FIELD AND NEAR-FIELD MIMO CHANNEL MODELS

	Far-field MIMO	Near-field MIMO
Wave model	Planar wave	Spherical wave
Channel sparsity	Angular-domain	Angle–distance domain
Steering vector	$\mathbf{a}_{\text{FF}}(\theta)$	$\mathbf{a}_{\text{NF}}(r,\theta)$
Channel model	$\sum \alpha_\ell \mathbf{a}_{\text{FF}}(\theta_\ell)$	$\sum \alpha_\ell \mathbf{a}_{\text{NF}}(r_\ell,\theta_\ell)$

III. KEY ENABLING METHODS FOR NEAR-FIELD COMMUNICATIONS

A. Channel Estimation

Channel estimation serves as the foundation for all subsequent signal processing tasks in wireless communications. In conventional far-field massive MIMO systems, two primary approaches have been widely adopted. First, *pilot-based schemes* such as LS and MMSE have been widely adopted, where in particular the MMSE estimator exploits long-term channel covariance information to improve estimation accuracy [11]. Second, *compressive sensing (CS)-based methods* leverage the angular-domain sparsity of far-field channels, formulating channel estimation as a sparse recovery problem using a DFT-based dictionary [12]. However, these approaches cannot be directly applied in the near-field regime of ELAA systems.

The planar-wave assumption underlying far-field models breaks down, and the channel exhibits *angle-distance domain sparsity* rather than angular sparsity. Moreover, in ELAA systems with hundreds or even thousands of antennas, acquiring sufficient channel statistics across all elements becomes practically infeasible, further limiting the applicability of statistical estimation methods. As a result, statistical methods become inaccurate, while conventional CS-based methods with DFT dictionaries fail to capture the range dependency of spherical wavefronts.

To address the above problem, polar-domain codebook based compressive sensing is proposed to exploit the angle-distance sparsity of spherical wavefront channels [7]. The construction of the polar-domain codebook relies on the Fresnel approximation [13], where the distance is approximated as

$$r^{(n)} \approx r - nd\theta + \frac{n^2 d^2 \left(1-\theta^2\right)}{2r}. \tag{8}$$

These approximation is derived from the Taylor expansion $\sqrt{1+x} \approx 1 + \frac{1}{2}x - \frac{1}{8}x^2$. In compressive sensing (CS)-based channel estimation, the recovery performance strongly depends on the correlation of the sensing codebook [14]. A lower coherence implies that the columns of coherence are more distinguishable, thereby improving the success probability of sparse recovery algorithms such as OMP or Basis Pursuit. Conversely, high coherence leads to ambiguity in identifying the correct channel support, which severely degrades the estimation accuracy. Therefore, the column coherence, defined as $\mu = \max \left|\mathbf{a}_{\text{NF}}^H(r_i,\theta_i)\,\mathbf{a}_{\text{NF}}(r_j,\theta_j)\right|$, should be seleted as small as possible. The approximated column coherence can be formulated as in [7]

$$\mu \approx \frac{1}{N}\left|\sum_{n=0}^{N} e^{jn\pi(\theta_i-\theta_j)+j\frac{2\pi}{\lambda}n^2d^2\left(\frac{1-\theta_i^2}{2r_i}-\frac{1-\theta_j^2}{2r_j}\right)}\right|. \tag{9}$$

By defining the distance ring as $\frac{1-\theta^2}{r} = \frac{1}{q}$, the non-linear phase term in the coherence is eliminated within each ring, which enables DFT-based angular sampling similar to the far-field case. Meanwhile, the spacing between adjacent distance rings can be controlled by using the Fresnel function to make the column coherence lower than a given threshold. This codebook effectively captures the polar-domain sparsity of the near-field channel, which enables sparse recovery algorithms such as OMP to achieve reliable performance. However, efficient channel estimation remains challenging, since the polar-domain codebook constructed from sampled angle–distance pairs results in a substantially larger size compared to the conventional angular-domain codebook.

To address these issues, recent works can be categorized into the following directions:

- **Distance-specific dictionary design**: constructing adaptive dictionaries that explicitly capture the distance-dependent phase variations of near-field channels [15], [16].
- **Side-information aided estimation**: incorporating additional knowledge such as user location or partial channel statistics to enhance estimation accuracy and reduce codebook size [17], [18].
- **Parametric channel estimation**: directly estimating physical parameters such as angle and distance using geometric channel models [19].
- **Learning-based methods**: employing deep neural networks or model-driven learning frameworks to leverage structural sparsity and nonlinear channel features [20]–[22].

B. Beam training

Beam training is a practical strategy to find strongest communication link without requiring full channel state information (CSI). Instead of explicitly estimating the channel, the BS and user sequentially calculate the correlation between channel and candidate beamforming from a predefined codebook. This approach significantly reduces pilot overhead and computational cost compared to exhaustive channel estimation.

It is important to note the fundamental distinction between beam training and channel estimation. Channel estimation attempts to reconstruct the complete channel vector (or matrix) $\mathbf{h}$. Beam training, on the other hand, bypasses full CSI acquisition and directly identifies a srongest spatial direction of channel through beam sweeping. Thus, channel estimation yields CSI but at high overhead, whereas beam training provides only the optimal beam direction with considerably lower complexity.

The primary objective of beam training is to select a transmit beam that maximizes a performance metric, commonly the received signal strength. Mathematically, given a codebook $\mathbf{W} = \{\mathbf{w}_1, \ldots, \mathbf{w}_{N_c}\}$, the optimal beam is chosen as

$$\mathbf{w}^\star = \arg\max_{\mathbf{w}\in\mathcal{W}} \left|\mathbf{h}^H\mathbf{w}\right|^2, \tag{10}$$

where $\mathbf{h}$ denotes the effective channel vector. This optimization ensures that the selected beam provides the strongest possible link under given channel conditions.

In conventional far-field systems, beam training is performed over an angular-domain codebook. The array response depends only on the angle of arrival, and discrete Fourier transform (DFT)-based codebooks are sufficient for sweeping. In practice, the 5G New Radio (NR) standard specifies two types of beam training procedures:

- **Type-I** : which is designed for low-rank transmission, typically rank-1, where each codeword corresponds to a directional beam on a predefined angular grid.
- **Type-II** : which is designed for higher-rank transmission, where multiple beams are simultaneously combined to capture multiple spatial paths.

Type-I training is more robust and incurs lower feedback overhead, while Type-II training enables finer beam adaptation at the cost of higher signaling overhead.

However, the planar-wave assumption no longer holds in near-field systems as explained above. This gives rise to a two-dimensional codebook indexed by both angular and distance parameters. Consequently, near-field beam training is inherently more challenging, as the codebook size grows significantly and novel hierarchical designs are required to balance accuracy and training overhead. To design the hierarchical beam training for XL-MIMO, Shi et al [8] provide the three fundamental criteria as follows:

- **Intra-layer** : In each hierarchical layer, the union of all codeword coverage regions should fully cover the entire possible channel
- **Inter-layer** : The coverage region of any codeword in the l-th layer should be completely contained in the union of several finer codeword regions in the $(l+1)$-th layer
- **Scalability** : Within each layer, all codewords should be generated from a reference codeword through rotation

To satisfy the above three criteria, the hierarchical beam training is constructed in the polar domain by representing each beam in the slope-intercept domain. Specifically, the phase term at each antenna element in (5) can be expressed as

$$\theta_n = \theta + \frac{\lambda(1-\theta^2)}{4r} n, \tag{11}$$

when antenna spacing d is equal to half of the wavelength λ. Then, the near-field steering vector can be expressed as

$$\mathbf{a}_{\mathrm{NF}}(r,\theta) = \frac{1}{\sqrt{N}} e^{-j\pi r} \left[e^{j\pi\theta_0}, e^{j\pi\theta_1}, \ldots, e^{j\pi\theta_{N-1}} \right]^T \tag{12}$$

Above equation (11) corresponds to a linear function with slope $k = \frac{\lambda(1-\theta_0^2)}{4r_0}$ and intercept $b = \theta_0$. By transforming the polar domain into the (k,b) domain, the codebook can be systematically designed such that: (i) each hierarchical layer fully covers the entire slope-intercept space, (ii) the coverage region of a coarse beam is refined by multiple beams in the next layer, and (iii) all codewords are generated via beam rotation to preserve scalability. Based on this slope-intercept domain representation, a codebook structure and a hierarchical beam search procedure are developed, which enable efficient near-field beam training while maintaining the coarse-to-fine search property.

Despite the advantages of the slope-intercept domain based hierarchical beam training, several challenges remain for practical implementation such as compatibility with the existing 3GPP codebook standards, as the near-field structure differs significantly from the conventional far-field DFT-based design. To overcome the challenges of extending conventional beam training methods into the near-field, one promising direction is the use of planar wave expansion [23]. The planar wave expansion provides a unified framework for characterizing both far-field and near-field propagation in XL-MIMO systems. Instead of treating the near-field channel as a purely spherical wave phenomenon, it represents the channel as a superposition of multiple plane waves arriving from different directions. This perspective allows the near-field channel to be approximated within the same angular domain framework as the far-field, thereby enabling the reuse of conventional DFT-based codebooks and beam training techniques.

C. CSI Feedback

In time division duplex systems, CSI acquisition is facilitated via channel reciprocity after estimating the downlink or uplink channel. However, in frequency division duplex systems, where uplink and downlink operate on different frequencies, CSI must be explicitly fed back from the UE to the BS. Therefore, CSI feedback schemes plays a crucial role and extensive research has been conducted in the far-field context. A straightforward method for CSI feedback is to quantize and transmit the estimated channel coefficients, but this requires an excessive number of bits. Therefore, codebook-based index feedback has become the dominant approach in practical systems.

Unlike channel estimation, the main requirement of CSI feedback is that for any possible channel realization, there should exist at least one codeword that maintains sufficiently high correlation with the true channel. This requirement can be expressed by the following objective:

$$\max_{\mathcal{C}} \min_{\mathbf{h}\in\mathcal{H}} \max_{\mathbf{c}\in\mathcal{C}} |\mathbf{h}^H\mathbf{c}|^2, \tag{13}$$

where $\mathcal{C}$ denotes the codebook and $\mathcal{H}$ represents the channel set.

Classical approaches include Grassmannian line packing, random vector quantization, and Lloyd-Max algorithm [24], [25], all of which aim to design codebooks with low mutual coherence on the complex unit sphere. However, due to the near-field effect, the steering vector depends on both angle and distance, which makes it difficult to directly apply the above codebook-based feedback methods that are designed for angular-domain sparsity. To this end, [9] analyzes the codebook quantization performance of near-field channels for both the ULA and the UPA, and subsequently proposes a novel codebook design which gaurantees the minimum correlation φ. Specifically, the correlation between adjacent codewords in the slope-intercept (k,b) domain is approximated using a polynomial formula, and a fitting function is derived with respect to the required minimum correlation φ.

$$f(\Delta k, \Delta b) \approx p\Delta k^2 N^4 + q\Delta b^2 N^2 + 1 \tag{14}$$

where the coefficients p and q can be obtained by the least square method.

IV. Conclusions

In this paper, we have provided a comprehensive overview of channel estimation, beam training, and CSI feedback for near-field XL-MIMO systems. We first highlighted that conventional DFT-based angular-domain approaches are inadequate in the near-field regime due to the presence of distance-dependent phase variations. To address this issue, a polar-domain representation was introduced, where distance rings enable DFT-based angular sampling and facilitate efficient channel estimation. We further discussed the fundamental differences between beam training and channel estimation, emphasizing that beam training aims to directly identify optimal beams rather than reconstructing the full channel.

Moreover, hierarchical beam training strategies in the polar domain were introduced, which effectively reduce training overhead while maintaining high resolution. For CSI feedback, we reviewed feedback aware codebook design where adjacent codeword correlations can be approximated by polynomial fitting functions to ensure reliable quantization performance.

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