

Signal as Token: Robust DOA Estimation in Complex Environments Aided by Transformer

Ziqi Wang[†], Zihan Cao[†], *Member IEEE*, Julian Xie^{*}, and *Member IEEE*, Zishu He

Abstract—Direction of Arrival (DOA) estimation, with applications in various fields, is a widely-researched problem. However, the lack of adaptation DOA estimation methods in the presence of various complex environments remains a significant challenge in the field. Conventional approaches heavily rely on manually engineered features and assumed array priors. Moreover, their performance is often unsatisfactory in the face of complex environments. In this paper, we propose a novel approach that harnesses the power of the Transformer to tackle the DOA estimation problem. The Transformer leverages the self-attention mechanism to effectively capture long-range dependency within data sequences. By employing the Transformer in the DOA estimation task and introducing a sensor-based attention mechanism tailored for DOA estimation, we provide evidence that the sensor-based attention output corresponds to a pseudo Singular Value Decomposition (pseudo-SVD) of the covariance matrix. Leveraging this mechanism enables us to capture more profound feature information within the received signals, leading to highly accurate DOA estimation. Furthermore, our proposed Transformer-based approach exhibits good adaptability in the presence of low signal-to-noise ratio, a limited number of snapshots, array errors, coherent sources, and broadband sources. Rigorous experiments conducted on synthetic and real-world datasets validate the effectiveness and generalization capability of our method. Additionally, our proposed method has also been proven effective in solving the problem of estimating the number of signal sources. Overall, this work presents a promising solution by seamlessly integrating the capabilities of the Transformer with the DOA estimation task, enabling accurate DOA estimation even in the most challenging scenarios.

Index Terms—Direction-of-Arrival (DOA) estimation, Transformer, Attention mechanism, Reconstruction.

I. INTRODUCTION

DIRECTION-of-arrival estimation is an extensively researched topic, finding applications in diverse domains such as radar [1], wireless communication [2], UAV localization [3], and sonar detection [4]. With the rapid development of related industries in recent years, DOA estimation has garnered substantial attention. Researchers have diligently focused on developing precise and dependable DOA estimation techniques to cater to the evolving requirements of specific scenes [5].

Classic approaches to Direction of Arrival (DOA) estimation encompass various methods such as array signal processing-

based beamforming [6], [7], maximum likelihood estimation [8]–[11], subspace-based methods [12]–[14], and the sparsity-inducing methods [15], [16]. These DOA estimation methods critically rely on the intricate statistical properties of the signals. They employ sophisticated signal processing techniques and robust parameter estimation algorithms to infer the precise direction information of the targets. By adeptly utilizing the received signals from the array, these methods effectively exploit the interplay between array geometry and signal statistics, resulting in accurate DOA estimation across diverse application domains.

However, factors such as low SNR, low snapshots, coherent signals, and broadband signals would affect estimation performance seriously. Taking the most classical subspace decomposition method [12]–[14] as an example, its core is to decompose the covariance matrix of the received signals into the signal subspace and the noise subspace, relying on the orthogonality between the noise component and the steering vectors for DOA estimation. In order to ensure orthogonality, the above method requires ideal factors (e.g., sufficiently high SNR, many snapshots). If one or more of these factors are not ideal, the performance of general estimation methods typically deteriorates significantly. Scholars have proposed various methods to solve these problems, such as using the MUSIC-like method [17] to deal with the estimation of DOA under low SNR, using the beamforming method [18] to deal with DOA under low snapshots estimation of the problem, utilizing Spatial Smoothing (SPS) [19] or Compressed Sensing (CS) [20] theory for DOA estimation of correlated signal sources, and employing frequency band division techniques [21] to handle DOA estimation of broadband signal sources. However, these methods often compromise resolution and struggle to accurately recover all sources when the number of sources is unknown.

In addition to the non-ideal factors above, in real-world scenarios, kinds of array errors, such as the inconsistency in amplitude and phase between channels, array element position errors, the mutual coupling, and directional pattern errors of array elements, which makes formidable challenges in accurately characterizing the array system. These factors undermine the ability to establish precise models, thereby exerting adverse effects on the performance of the aforementioned DOA estimation methods. In order to address this challenge, different array error modeling methods are proposed to estimate DOA [22], [23]. Nevertheless, it is crucial to note that most array error modeling methods rely on stringent assumptions, and any deviation from these assumptions can render the models ineffective. Moreover, in practical scenarios,

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the presence of multiple concurrent errors can give rise to complex and intertwined effects, which may substantially deviate from the idealized assumptions. These deviations inevitably exert a profound influence on the performance of DOA estimation algorithms, leading to compromised accuracy.

In response to these challenges, researchers have explored the application of machine learning (ML) techniques to address the aforementioned issues. ML-based approaches, such as Support Vector Machines (SVM) [24], [25], Support Vector Regression (SVR) [26], [27], and Radial Basis Function (RBF) [28], [29], have emerged as promising solutions, showcasing enhanced modeling capabilities. These data-driven methods operate by leveraging training data, where input data and corresponding angle labels are used to establish a non-linear mapping from inputs to outputs. Notably, these methods exhibit a distinct advantage by not relying on assumptions regarding array geometry, thus demonstrating robustness in the face of non-ideal factors. In fact, researches [27] have substantiated their superiority over traditional subspace-based methods (e.g., MUSIC) in terms of effectiveness and performance in the DOA estimation task.

Nonetheless, ML-based methods still exhibit notable limitations. Although they showcase commendable adaptability to array geometries, the efficacy of these estimation approaches primarily hinges upon the learning proficiency and generalization prowess of models. A pressing concern lies in the fact that the majority of DOA estimation works employing machine learning techniques predominantly rely on synthetic data, which may diverge from the complexities inherent in real-world scenarios. Consequently, such disparities can engender a decline in performance for these methods when confronted with practical applications.

In recent years, there has been rapid development and widespread application of deep learning-based (DL-based) methods in various fields, such as image classification, image generation, and sequential modeling. These methods leverage deep neural network architectures, including Convolutional Neural Networks (CNNs) [30]–[32], Recurrent Neural Networks (RNNs) [33], [34], and Transformers [35]–[39], to learn from data and make accurate predictions. DL-based methods exhibit stronger capabilities in fitting complex mappings and extracting deeper features compared to traditional machine learning approaches. Given the advantages of deep learning, researchers have also explored its potential in solving the DOA estimation problem. Notably, Liu *et al.* [40] introduced the use of an autoencoder to address the challenge of subspace partitioning. An autoencoder is employed to divide the input covariance matrix into multiple angle grids, enabling coarse classification of the DOA on the grid for each source. Fine-grained angle estimation within each grid was achieved using a Multilayer Perceptron (MLP), and the final results were obtained through bilinear interpolation of the predictions of the MLP. It demonstrated promising performance in general DOA estimation tasks and showed some adaptability to array errors. Nonetheless, it not only needs tedious two-stage training and faces challenges in scenarios with low signal-to-noise ratios and coherent sources. Furthermore, the heavy reliance on classifiers in the overall model architecture limited its

performance due to grid constraints. Shmuel *et al.* [41] utilized a Deep Convolutional Neural Network (DCNN) to reconstruct the covariance matrix of received signals. This reconstructed matrix was then integrated into traditional subspace-based DOA estimation methods, combining the interpretability of traditional methods with the powerful learning capabilities of deep models. However, it should be noted that the output matrix lacks explicit constraints, and the model can only be trained with differentiable traditional methods.

Based on the above, previous DL-based DOA estimation works have often been limited to MLP or shallow CNN, overlooking the impact of deep models on DOA estimation. Furthermore, most previous works have restricted DOA estimation to angle grids, transforming DOA estimation into a classification problem on the grid. Although these approaches reduce the learning difficulty for the network, they can lead to inaccurate DOA estimation. Transformer was initially introduced in the field of natural language processing (NLP) [39], [42] and has since been applied to natural images [37], medical images [43], [44], sequential modeling [45], and content generation [35], [36]. Importantly, the attention mechanism is the key component of the Transformer, calculating an element-wise correlation matrix thereby assigning different weights to different elements. As a result, the attention mechanism allows the model to focus on the parts of the data that are crucial for the task. Therefore, incorporating the Transformer architecture into DOA estimation has tremendous potential.

Note that, the obtaining of the traditional attention map is computed by covariance-like matrix multiplication on the channel dimension, thereby resulting in snapshot-length square attention. However, the covariance matrix generated by signals is proven to be effective to extract DOA features by most model-based methods but is in conflict with the traditional snapshot-length square attention. Inspired by this finding, we propose a novel attention mechanism that models the correlation of sensors and outputs sensor-length square attention. By utilizing the attention mechanism, the proposed model can capture complex relationships and dependencies, while achieving more accurate and robust DOA estimation. Additionally, the flexibility of the proposed attention mechanism enables the model to adapt to various data patterns and effectively handle challenging scenarios.

The contributions of this paper can be summarized in the following five folds:

- 1) To the best of our knowledge, we introduce the Transformer architecture for the first time in the context of DOA estimation.
- 2) Instead of the conventional grid point classification, we change the modeling objective into direct DOA regression. This modification allows the network to estimate DOA more accurately and minimize errors.
- 3) Furthermore, we enhance the original Transformer architecture by incorporating the proposed effective attention mechanism. This modification enables the model to learn the effective feature representations from the covariance matrix. Moreover, the proposed attention mechanism owns better interpretability.

- 4) Extensive experiments on the DOA task including low-SNR, limited snapshots, coherent, broadband sources, and array errors show that our proposed method can obtain the least DOA estimation error and is robust to these non-ideal factors.
- 5) We validate the effectiveness of our proposed model on real-world datasets, which enhances the practicability of our model.

The rest of the paper is organized as follows: in Sec. II, we present the signal model and traditional attention mechanism. In Sec. III, we introduced the proposed sensor-based attention mechanism. In Sec. IV, we present simulation results in various situations. In Sec. V, we summarize and highlight our conclusions.

II. PRELIMINARY

A. Conventional Signal Modeling

Assuming K signals with the center frequency of f impinge on a uniform line array composed of M omni-directional sensors, with inter-sensor spacing $d = \frac{\lambda}{2}$, where λ represents the wavelength, and their DOAs denoted as $\theta_1, \dots, \theta_K$. The k -th source signal can be represented as $s_k(t)$. The array output is obtained by uniformly sampling the received signal $\mathbf{x}(t)$ at N time instants, resulting in a total of N snapshots. The received vector can be represented as follows: $\mathbf{X} = [\mathbf{x}(1), \dots, \mathbf{x}(N)]$. The array outputs are contaminated by the zero-mean Gaussian noise $\mathbf{v}(n)$.

In the absence of array errors, the mapping from the wave direction to the array output should be accurately established. This means that there exists a relationship between the array output and the signal input, which can be expressed as follows,

$$\mathbf{x}(n) = \sum_{k=1}^K \mathbf{a}(\theta_k) s_k(n) + \mathbf{v}(n), n = 1, \dots, N \quad (1)$$

Its matrix form can be expressed as follows,

$$\mathbf{X} = \mathbf{A}\mathbf{S} + \mathbf{V}, \quad (2)$$

where,

$$\mathbf{X} = \begin{bmatrix} x_1(1) & x_1(2) & \cdots & x_1(N) \\ x_2(1) & x_2(2) & \cdots & x_2(N) \\ \vdots & \vdots & \ddots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ x_M(1) & x_M(2) & \cdots & x_M(N) \end{bmatrix} \in \mathbb{C}^{M \times N}, \quad (3)$$

$$\mathbf{S} = \begin{bmatrix} s_1(1) & s_1(2) & \cdots & s_1(N) \\ s_2(1) & s_2(2) & \cdots & s_2(N) \\ \vdots & \vdots & \ddots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ s_K(1) & s_K(2) & \cdots & s_K(N) \end{bmatrix} \in \mathbb{C}^{K \times N}, \quad (4)$$

$$\mathbf{V} = \begin{bmatrix} v_1(1) & v_1(2) & \cdots & v_1(N) \\ v_2(1) & v_2(2) & \cdots & v_2(N) \\ \vdots & \vdots & \ddots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ v_M(1) & v_M(2) & \cdots & v_M(N) \end{bmatrix} \in \mathbb{C}^{M \times N}, \quad (5)$$

$$\mathbf{A} = [\mathbf{a}(\theta_1) \quad \mathbf{a}(\theta_2) \quad \cdots \quad \mathbf{a}(\theta_K)] \in \mathbb{C}^{M \times K}, \quad (6)$$

where $x_i(j)$ represents the j -th snapshot received by the i -th array element, $s_i(j)$ represents the j -th snapshot of the i -th source signal, and $v_i(j)$ represents the j -th snapshot noise of the i -th array element.

However, practical arrays suffer from various errors, such as the inconsistency in amplitude and phase between channels, array element position errors, the mutual coupling, and directional pattern errors of array elements. The presence of these errors introduces the steering vector $\mathbf{a}(\theta)$ mismatch, rendering the ideal assumptions invalid. The amplitude and phase inconsistency between channels is generally unrelated to the DOA of the signal. Thus, the array output with this type of errors can be modeled as,

$$\mathbf{x}(n) = [\mathbf{L}\mathbf{A}]\mathbf{s}(n) + \mathbf{v}(n), \quad (7)$$

where,

$$\mathbf{L} = \text{diag}[l_1, l_2, \dots, l_m, \dots, l_M] \in \mathbb{C}^{M \times M}, \quad (8)$$

l_m is a complex number that represents amplitude and phase errors for the m -th sensor. The array element position errors will introduce a phase error with directional dependence. Therefore, the observed data of the array can be modeled as,

$$\mathbf{x}(n) = [\mathbf{A} \odot \mathbf{B}]\mathbf{s}(n) + \mathbf{v}(n), \quad (9)$$

where \odot represents the Hadamard product.

$$\mathbf{B} = [\mathbf{b}(\theta_1) \quad \mathbf{b}(\theta_2) \quad \cdots \quad \mathbf{b}(\theta_K)] \in \mathbb{C}^{M \times K}, \quad (10)$$

is the matrix representing the errors introduced by array element positions, where the error vector can be represented as,

$$\mathbf{b}(\theta_k) = [e^{j\Delta\phi_1(\theta_k)}, \dots, e^{j\Delta\phi_M(\theta_k)}]^T, \quad (11)$$

$\Delta\phi_m(\theta_k)$ is the phase error introduced by the relative position of the m -th element respect to the k -th impinging direction. The

mutual coupling between the array elements enables the array output to be represented as,

$$\mathbf{x}(n) = \mathbf{C}\mathbf{A}\mathbf{s}(n) + \mathbf{v}(n). \quad (12)$$

where \mathbf{C} is the mutual coupling matrix,

$$\mathbf{C} = \begin{bmatrix} c_{11} & c_{12} & \cdots & c_{1M} \\ c_{21} & c_{22} & \cdots & c_{2M} \\ \vdots & \vdots & \ddots & \vdots \\ c_{M1} & c_{M2} & \cdots & c_{MM} \end{bmatrix} \in \mathbb{C}^{M \times M}. \quad (13)$$

The directional pattern error mainly refers to the gain errors between the actual directional pattern and the ideal directional pattern. The errors it introduces also have directional dependence. The array output considering this errors can be represented as,

$$\mathbf{x}(n) = [\mathbf{A} \odot \mathbf{P}]\mathbf{s}(n) + \mathbf{v}(n), \quad (14)$$

where,

$$\mathbf{P} = [\mathbf{p}(\theta_1) \quad \mathbf{p}(\theta_2) \quad \cdots \quad \mathbf{p}(\theta_K)] \in \mathbb{C}^{M \times K}, \quad (15)$$

$$\mathbf{p}(\theta) = [p_0(\theta), \cdots, p_{M-1}(\theta)]^T. \quad (16)$$

When all the aforementioned non-ideal factors are presented, the receiving model of the array can be expressed as,

$$\mathbf{x}(n) = \{\mathbf{L}[\mathbf{C}(\mathbf{A} \odot \mathbf{P} \odot \mathbf{B})]\}\mathbf{s}(n) + \mathbf{v}(n). \quad (17)$$

In this case, the steering matrix of the array, also known as the array response matrix, is modified to be,

$$\tilde{\mathbf{A}} = \mathbf{L}[\mathbf{C}(\mathbf{A} \odot \mathbf{P} \odot \mathbf{B})]. \quad (18)$$

Therefore, we obtain the following equations,

$$\mathbf{x}(n) = \tilde{\mathbf{A}}\mathbf{s}(n) + \mathbf{v}(n), \quad (19)$$

$$\tilde{\mathbf{a}}(\theta) = \mathbf{L}[\mathbf{C}(\mathbf{a}(\theta) \odot \mathbf{p}(\theta) \odot \mathbf{b}(\theta))]. \quad (20)$$

It can be clearly observed that the error in the steering vector is frequency and direction-dependent. Despite the modeling approaches mentioned above, it is often challenging to accurately model for the complex real-world environments. Thus, approximation and simplification methods to the data modeling are commonly employed in many DOA estimation methods. They face the problem of a sharp decline in DOA estimation performance once approximation and simplification fail. In addition to array errors affecting the accuracy of DOA estimation, the correlation between signals and broadband signals mentioned earlier can also impact the estimation performance. Traditional methods designed for correlated or broadband signals often sacrifice resolution, which can affect the estimation accuracy and may not meet the specific requirements of practical scenarios. Therefore, it is crucial to explore a framework or approach that can effectively address these problems.

B. Traditional Attention

We first review the traditional attention mechanism. The attention mechanism can be seen as a data-adaptive weighted operation. It extracts different parts weighted by the covariance-like attention map on the spatial dimension, which can be formulated as follows,

$$\mathbf{A}_S = \mathbf{Q}^T \mathbf{K}, \quad (21)$$

where $\mathbf{A}_S \in \mathbb{R}^{N \times N}$ is the covariance-like attention map, M is the number of feature channels. $\mathbf{Q}, \mathbf{K}, \mathbf{V} \in \mathbb{R}^{M \times N}$ are named query, key, value and defined as follows,

$$\mathbf{Q}, \mathbf{K}, \mathbf{V} = \mathbf{W}^Q g(\mathbf{X}), \mathbf{W}^K \mathbf{X}, \mathbf{W}^V \mathbf{X}. \quad (22)$$

The $\mathbf{W}^i (i = Q, K, V)$ is a linear projection weight matrix¹, which is responsible for projecting the input feature $\mathbf{X} \in \mathbb{R}^{M \times N}$ into three different high-dimensional spaces. g is a matrix block transformation. When g is a specific transformation rather than an identity transformation (i.e., $\mathbf{X} = g(\mathbf{X})$), the attention is a cross-attention otherwise is a self-attention. Then the output of the weighted attention operation is defined as follows,

$$\mathbf{O} = \text{Softmax} \left(\frac{\mathbf{A}_S}{\sqrt{M}} \right) \mathbf{V}^T, \quad (23)$$

where Softmax is applied to ensure the attention map is probabilistic in each row. This equation shows that the information in \mathbf{V} space is projected into \mathbf{O} space by attention map \mathbf{A}_S .

In the context of DOA estimation, the attention map $\mathbf{A}_S \in \mathbb{R}^{N \times N}$ is obtained by a matrix multiplication by two projected matrixes. It models the relationship within each snapshot, then results in $N \times N$ attention map.

III. PROPOSED SYSTEM MODEL

A. Math Notation

In this section, we elaborate on the overall math notion represented in Tab. I.

TABLE I: Math notation.

Notation	Explanation
\mathbf{X}	Received signals.
\mathbf{x}	The input of the Transformer layer (i.e., tokens).
\mathbf{R}	Covariance matrix obtained by Eq. 30.
$\mathbf{Q}, \mathbf{K}, \mathbf{V}$	Query, Key, Value defined in Eq. 22.
$\mathbf{A}_S, \mathbf{A}_R, \mathbf{A}_I$	Attention maps formed in Eqs. 21, 31.
\mathbf{O}	Output features from attention defined in Eq. 23.
$(\cdot)^H$	Matrix conjugate transpose.
$(\cdot)^*$	Matrix conjugate.
$(\cdot)^T$	Matrix transpose.
K	Number of sources.
M	Number of sensors.
N	Number of snapshots.
$\text{Re}(\cdot)$	The real part of a complex-valued matrix.
$\text{Im}(\cdot)$	The imaginary part of a complex-valued matrix.
$f(\cdot)$	The proposed Transformer model.

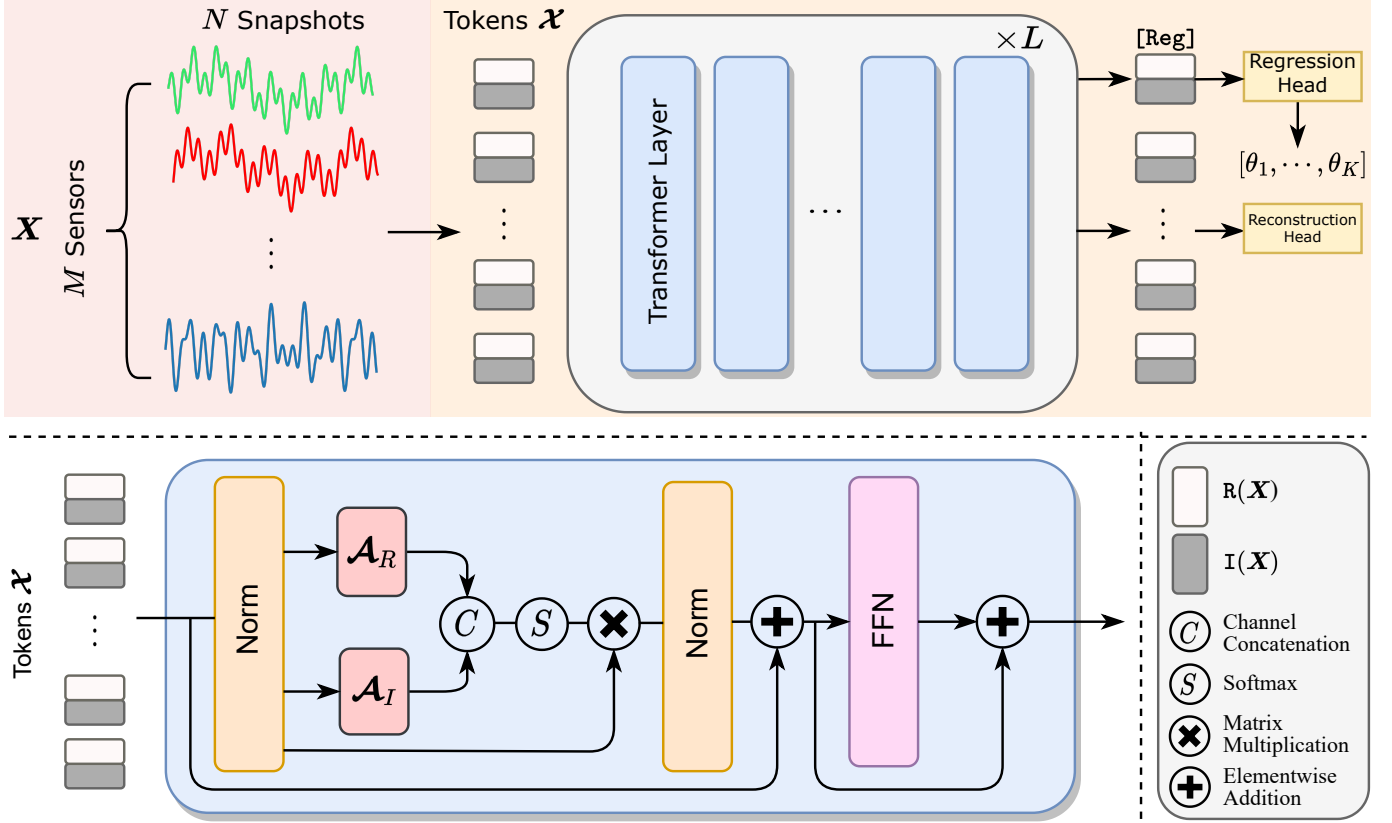


Fig. 1: Overview of the proposed model architecture. **Upper panel:** The original signal sources are first tokenized into tokens \mathcal{X} and stacked with the real and imaginary parts on the sensor dimension. The tokens are concatenated with a $[\text{reg}]$ token for final regression and are fed into the L Transformer layers. Then the $[\text{reg}]$ token is extracted to a regression head to output the final DOA. **Bottom panel:** Illustration of our proposed sensor-based attention module.

B. Overall Architecture

We first introduce the overall architecture illustrated in Fig. 1. Our DOA estimation deep architecture is a pure Transformer whose input signals \mathbf{X} are shaped as $\mathbb{C}^{M \times N}$. The Transformer architecture is formed by L Transformer layers. The first layer takes the tokenized signal tokens $\mathcal{X} \in \mathbb{R}^{M \times 2N}$ as input and processes the tokens to feed into the next layer. The tokens \mathcal{X} are defined as follows,

$$\mathcal{X} = [\mathbf{R}(\mathbf{X}) \ \mathbf{I}(\mathbf{X})], \quad (24)$$

where $[\cdot]$ is concatenating along the last dimension. We will elaborate on the rationale behind this concatenation in Section III-C. Before feeding the first layer, we add a learnable token $[\text{reg}] \in \mathbb{R}^{M \times 1}$ into the original tokens for regression DOA. After L layers, the output of our proposed model is shaped as $\mathbb{R}^{M \times (2N+1)}$. We take out the regression DOA token and send it to the regression head, which is a simple MLP, to get an estimated DOA. The rest of the $2N$ tokens are projected into the tokenized signal space to reconstruct the original tokens. The aim of the reconstruction is to constrain the attention map in high-dimensional space (see Corollary. 3.1).

The detailed design of each Transformer layer is shown in the bottom panel of Fig. 1. Firstly, the input tokens are fed

into a Layernorm, which operates normalization on channel dimension (i.e., M dimension in the DOA context). Then two outcomes $\mathcal{A}_R, \mathcal{A}_I$ of attention mechanisms are possessed and concatenated together into another Layernorm. To facilitate training stability, a shortcut is enabled, which adds the input to the normalized intermediate features. After that, the features are fed into a Feed Forward Network (FFN) to enhance the feature representation. The FFN is implemented by an MLP with three fully-connected (FC) layers. The middle FC layer doubles the number of channels and the last FC layers reduce the number of channels back to M . A GELU activation [46] is inserted between the first and the second FC layer. We adopt the simple gate proposed in Restormer [47]. Similarly, another shortcut is added. The overall pipeline can be formulated as follows,

$$\mathcal{X}_{\text{norm}}^l = \text{Norm}(\mathcal{X}^l), \quad (25a)$$

$$\mathcal{X}_{\text{attn}}^l = \text{Softmax} \left(\frac{[\mathcal{A}_R \ \mathcal{A}_I]^T}{\sqrt{2M}} \right) \mathbf{v}, \quad (25b)$$

$$\mathcal{X}_{\text{norm2}}^l = \text{Norm}(\mathcal{X}_{\text{attn}}^l) + \mathcal{X}^l, \quad (25c)$$

$$\mathcal{X}_{\text{FFN}}^l = \text{FFN}(\mathcal{X}_{\text{norm2}}^l), \quad (25d)$$

$$\mathcal{X}^{l+1} = \mathcal{X}_{\text{FFN}}^l + \mathcal{X}_{\text{norm2}}^l. \quad (25e)$$

Superscript l denotes the l -th layer of the Transformer network. The training objective of our model is regression rather than

¹For simplicity, we omit the bias part here.

classification in [40] nor the rectified covariance matrix \mathcal{R} in [41]. Our training objective contains three terms: regression, reconstruction, and regularization objectives, which can be formulated as corresponding three loss functions,

$$\mathcal{L}_{reg} = \|\text{MLP}_{reg}(f(\mathcal{X})), \text{DOA}\|_2^2, \quad (26)$$

$$\mathcal{L}_{recon} = \|\text{MLP}_{recon}(f(\mathcal{X})), \mathcal{X}\|_2^2, \quad (27)$$

$$\mathcal{L}_{psvd} = \|\mathbf{V}^T \mathbf{V} - 2\mathbf{E}\|_2^2 + \|\mathbf{V} \mathbf{V}^T - 2\mathbf{E}\|_2^2. \quad (28)$$

The MLP_{reg} , MLP_{recon} are regression head and reconstruction head, respectively. DOA is used as the label for supervising the training. \mathcal{L}_{psvd} is a regularization loss which regularizes the attention output can be pseudo singular value decomposition (see more details in Theorem 3.3). In the training phase, we optimize the combination of the three losses together which is denoted as follows,

$$\mathcal{L}_{total} = \mathcal{L}_{reg} + \mathcal{L}_{recon} + 0.1\mathcal{L}_{psvd}. \quad (29)$$

C. Effective Sensor-based Attention

Due to the success of many model-based methods, they often form the covariance matrix²,

$$\mathcal{R} = \mathbf{X} \mathbf{X}^H, \quad (30)$$

and process it to extract DOA-related features (e.g., decomposing into noise and signal subspaces). Note the similarity between the commonly used covariance matrix and the attention map, it is easy to find that the covariance matrix links the relations within sensors rather than snapshots brought by the attention map. We argue that the traditional attention that models relationships among snapshots is insufficient and ineffective.

We propose a novel sensor-based covariance-like attention mechanism to extract features from the well-studied signal covariance matrix \mathcal{R} . The attention map is divided into two terms (i.e., \mathcal{A}_R , \mathcal{A}_I) to model the real part and imaginary part of the covariance matrix. The division formula is formed as follows,

$$\mathcal{A} := [\mathcal{A}_R \ \mathcal{A}_I] \in \mathbb{R}^{M \times 2M}. \quad (31)$$

\mathcal{A} is a tensor concatenated by \mathcal{A}_R and \mathcal{A}_I , which means the real and imaginary parts are stacked on the last dimension. With this division, we can model the covariance matrix \mathcal{R} in attention. The traditional attention can be reformulated into our sensor-based attention as follows,

$$\mathcal{Q}_R, \mathcal{K}_R = \mathbf{W}_R^Q g(\mathcal{X}), \mathbf{W}_R^K \mathcal{X}, \quad (32a)$$

$$\mathcal{Q}_I, \mathcal{K}_I = \mathbf{W}_I^Q g(\mathcal{X}), \mathbf{W}_I^K \mathcal{X}, \quad (32b)$$

$$\mathbf{V} = \mathbf{W}^V \mathcal{X}, \quad (32c)$$

$$\mathcal{A}_R = \mathcal{Q}_R \mathcal{K}_R^T, \quad (32d)$$

$$\mathcal{A}_I = \mathcal{Q}_I \mathcal{K}_I^T, \quad (32e)$$

$$\mathcal{A} = [\mathcal{A}_R \ \mathcal{A}_I], \quad (32f)$$

$$\mathcal{O} = \text{Softmax} \left(\frac{\mathcal{A}^T}{\sqrt{2M}} \right) \mathbf{V}, \quad (32g)$$

where \mathcal{X} is the input of the module from the previous Transformer layer³, g is a matrix block transformation. $\mathbf{W}_j^i, i = (Q, K, V), j = (R, I, \emptyset)$ are projection weights that project the inputs into a high-dimensional space. Based on the calculation of $\mathcal{A}_R, \mathcal{A}_I$, the input of the first Transformer layer is the tokenized signal that the real and imaginary parts are stacked along the snapshot dimension (i.e., $[\mathbf{R}(\mathbf{X}) \ \mathbf{I}(\mathbf{X})]$). Specifically, taking the first transformer layer as an example, when computing \mathcal{A}_R , g is the identity transformation,

$$g(\mathcal{X}) = \mathcal{X} = [\mathbf{R}(\mathbf{X}) \ \mathbf{I}(\mathbf{X})]. \quad (33)$$

When computing \mathcal{A}_I ,

$$g(\mathcal{X}) = [\mathcal{X}_{(N+1:2N)} \ -\mathcal{X}_{(1:N+1)}], \quad (34)$$

where $(m : n)$ are indexing operation from index m to n . So our sensor-based attention is hybrid attention (i.e., self-attention and cross-attention). According to the above, the covariance matrix can be modeled in our sensor-based attention,

$$\begin{aligned} \mathcal{R} = & \underbrace{[\mathbf{R}(\mathbf{X}) \ \mathbf{I}(\mathbf{X})] \cdot \begin{bmatrix} \mathbf{R}(\mathbf{X})^T \\ \mathbf{I}(\mathbf{X})^T \end{bmatrix}}_{\mathcal{A}_R} + j \underbrace{[\mathbf{I}(\mathbf{X}) \ -\mathbf{R}(\mathbf{X})] \cdot \begin{bmatrix} \mathbf{R}(\mathbf{X})^T \\ \mathbf{I}(\mathbf{X})^T \end{bmatrix}}_{\mathcal{A}_I} \end{aligned} \quad (35)$$

We present the theorems and prove the equality of the produced attention map \mathcal{A} and the stacked covariance matrix $[\mathbf{R}(\mathcal{R}) \ \mathbf{I}(\mathcal{R})]$.

Theorem 3.1 (Covariance real part equality theorem): Given a complex-valued signal input \mathbf{X} , the sensor-based attention first term \mathcal{A}_R equals the real part $\mathbf{R}(\mathcal{R})$ of the covariance matrix for the complex-valued signal.

Proof 3.1: Equality can be proven by using the property of complex-valued matrix: $\mathbf{R}(\mathbf{X}^H) = \mathbf{R}(\mathbf{X})^T, \mathbf{I}(\mathbf{X}^H) = -\mathbf{I}(\mathbf{X})^T$. Then, the \mathcal{A}_R can be derived by following equations,

$$\mathcal{A}_R = \mathbf{R}(\mathbf{X}) \cdot \mathbf{R}(\mathbf{X})^T + \mathbf{I}(\mathbf{X}) \cdot \mathbf{I}(\mathbf{X})^T \quad (36a)$$

$$= \mathbf{R}(\mathbf{X}) \cdot \mathbf{R}(\mathbf{X}^H) + \mathbf{I}(\mathbf{X}) \cdot \mathbf{I}(\mathbf{X}^H) \quad (36b)$$

$$= \mathbf{R}(\mathbf{X} \mathbf{X}^H) = \mathbf{R}(\mathcal{R}) \quad (36c)$$

Theorem 3.2 (Covariance imaginary part equality theorem): Given a complex-valued signal input \mathbf{X} , the sensor-based attention second term \mathcal{A}_I equals the imaginary part $\mathbf{I}(\mathcal{R})$ of the covariance matrix for the complex-valued signal.

Proof 3.2: Similar to Proof. 3.1, equality can be proven by using the property of complex-valued matrix, then the \mathcal{A}_I can be derived by following equations,

$$\mathcal{A}_I = -\mathbf{R}(\mathbf{X}) \cdot \mathbf{I}(\mathbf{X})^T + \mathbf{I}(\mathbf{X}) \cdot \mathbf{R}(\mathbf{X})^T \quad (37a)$$

$$= \mathbf{R}(\mathbf{X}) \cdot \mathbf{I}(\mathbf{X}^H) + \mathbf{I}(\mathbf{X}) \cdot \mathbf{R}(\mathbf{X}^H) \quad (37b)$$

$$= \mathbf{I}(\mathbf{X} \mathbf{X}^H) = \mathbf{I}(\mathcal{R}) \quad (37c)$$

We find that our sensor-based attention can be pseudo singular value decomposed, which enhances interpretability.

²For the sake of brevity, we have omitted the denominator N , which is used to divide the variable \mathcal{R} .

³We omit the superscript l for clear expression.

Theorem 3.3 (Sensor-based attention pseudo-SVD theorem): Considering a well-trained Transformer model, the sensor-based attention \mathcal{A} can approximate the stacked covariance matrix $[\mathbf{R}(\mathcal{R}) \ \mathbf{I}(\mathcal{R})]$. The output of the attention module \mathcal{O} can be singular value decomposition (SVD) into $\mathbf{U}\mathbf{\Sigma}\mathbf{V}^H = \left(\frac{\mathbf{T}^H\mathbf{Q}^*}{\sqrt{2}}\right)\mathbf{\Sigma}\left(\frac{\mathbf{Q}^T\mathbf{V}}{\sqrt{2}}\right)^H$, where the \mathbf{Q} and $\mathbf{\Sigma}$ are the eigenvectors and eigenvalues of \mathcal{R} , respectively. $\mathbf{T} = [\mathbf{E} \ \mathbf{J}]$, where \mathbf{E} is the unit matrix and $\mathbf{J} = j \cdot \mathbf{E}$.

It means that the output of the proposed attention module is in the space spanned by the (projected) signal and noise eigenvectors. Furthermore, the eigenvalues in $\mathbf{\Sigma}$ define the importance of the eigenvectors. Akin to the MUSIC algorithm, if the eigenvalue is large, the spanned space is dominated by the corresponding eigenvector, which forces the model to concentrate on the vital eigenvectors. We prove this theorem as follows.

Proof 3.3: If the Transformer is trained converged, the output of the attention module is obtained and defined as,

$$\mathcal{O} = \mathcal{A}^T \mathbf{V} = [\mathbf{R}(\mathcal{R}) \ \mathbf{I}(\mathcal{R})]^T \mathbf{V} = \begin{bmatrix} \mathbf{R}(\mathcal{R})^T \mathbf{V} \\ \mathbf{I}(\mathcal{R})^T \mathbf{V} \end{bmatrix} \quad (38)$$

Then we define the pseudo-complex-value output of \mathcal{O} as,

$$\hat{\mathcal{O}} = \mathbf{R}(\hat{\mathcal{O}}) + j\mathbf{I}(\hat{\mathcal{O}}) = \mathbf{T}\mathcal{O}. \quad (39)$$

Then we can get,

$$\mathbf{R}(\hat{\mathcal{O}}) = \mathbf{R}(\mathcal{R})^T \mathbf{V}, \quad (40a)$$

$$\mathbf{I}(\hat{\mathcal{O}}) = \mathbf{I}(\mathcal{R})^T \mathbf{V}, \quad (40b)$$

The covariance matrix can be eigen decomposed as follows,

$$\mathcal{R} = \mathbf{Q}\mathbf{\Sigma}\mathbf{Q}^H. \quad (41)$$

We can reformulate the output into,

$$\hat{\mathcal{O}} = \mathbf{R}(\mathcal{R})^T \mathbf{V} + j\mathbf{I}(\mathcal{R})^T \mathbf{V} \quad (42a)$$

$$= (\mathbf{R}(\mathcal{R})^T + j\mathbf{I}(\mathcal{R})^T) \mathbf{V} \quad (42b)$$

$$= \mathcal{R}^T \mathbf{V} \quad (42c)$$

$$= (\mathbf{Q}\mathbf{\Sigma}\mathbf{Q}^H)^T \mathbf{V}. \quad (42d)$$

Refer to Eq. 39, equality can be derived as follows,

$$(\mathbf{Q}\mathbf{\Sigma}\mathbf{Q}^H)^T \mathbf{V} = \mathbf{T}\mathcal{O} \quad (43a)$$

$$\Rightarrow \mathcal{O} = \mathbf{T}^\dagger \mathbf{O}^* \mathbf{\Sigma} \mathbf{Q}^T \mathbf{V} \quad (43b)$$

$$= \frac{1}{2} \mathbf{T}^H \mathbf{Q}^* \mathbf{\Sigma} \mathbf{Q}^T \mathbf{V} \quad (43c)$$

We prove this by considering $\frac{\mathbf{T}^H \mathbf{Q}^*}{\sqrt{2}}$ and $\frac{(\mathbf{Q}^T \mathbf{V})^H}{\sqrt{2}}$ as the unitary matrixes \mathbf{U} and \mathbf{V} , respectively. The new unitary matrix still holds the orthogonality that can be proven following,

$$\mathbf{U}\mathbf{U}^H = \frac{1}{2} \mathbf{T}^H \mathbf{Q}^* \mathbf{Q}^T \mathbf{T} = \frac{1}{2} \mathbf{T}^H (\mathbf{Q}\mathbf{Q}^H)^* \mathbf{T} \quad (44a)$$

$$= \frac{1}{2} \mathbf{T}^H \mathbf{T} = \mathbf{E} \quad (44b)$$

$$\mathbf{U}^H \mathbf{U} = \frac{1}{2} \mathbf{Q}^T \mathbf{T} \mathbf{T}^H \mathbf{Q}^* = (\mathbf{Q}^T \mathbf{Q})^* = (\mathbf{Q}^H \mathbf{Q})^* \quad (44c)$$

$$= \mathbf{E} \quad (44d)$$

Consequently, to ensure that the \mathbf{V} matrix holds the orthogonality, we can add another regularization term $\|\mathbf{V}^T \mathbf{V} - 2\mathbf{E}\|_2^2$. The rationale can be proven as follows,

$$\mathbf{V}\mathbf{V}^H = \frac{1}{2} \mathbf{V}^H \mathbf{Q}^* \mathbf{Q}^T \mathbf{V} = \frac{1}{2} \mathbf{V}^T (\mathbf{Q}\mathbf{Q}^H)^* \mathbf{V} \quad (45a)$$

$$= \frac{1}{2} \mathbf{V}^T \mathbf{V}, \quad (45b)$$

$$\mathbf{V}^H \mathbf{V} = \frac{1}{2} \mathbf{Q}^T \mathbf{V} \mathbf{V}^T \mathbf{Q}^*. \quad (45c)$$

Similarly, $\frac{1}{2} \mathbf{V}^T \mathbf{V}$ and $\frac{1}{2} \mathbf{V} \mathbf{V}^T$ should all be unit matrixes. As presented in Eq. 28, after performing regularization loss, the matrix \mathbf{V} can hold the orthogonality.

Another by-product of our sensor-based attention is the reduction of memory. It can be seen that the memory complexity of the traditional attention is $\mathcal{O}(N^2)$, so when the number of snapshots is large (e.g. usually 1000 or even larger) or the model is deep, the memory consumption is unaffordable. While our sensor-based attention is $\mathcal{O}(2M^2) \approx \mathcal{O}(M^2)$ memory complexity, it is more device friendly.

D. Sensor-based Attention on High Dimension

According to the theory of information bottleneck [48], [49], the model tends to drop out useless information for the training objective, which naturally forms an information bottleneck. In our context, the attention maps \mathcal{A} are in high-dimensional space which is not bounded. In other words, the high-dimensional \mathcal{X} may suffer information loss when the training objective is just the DOA regression.

Corollary 3.1 (High-dimension attention map constrain): The attention maps $\mathcal{A}_R, \mathcal{A}_I$ are bounded to obtain the lossless information of covariance matrix \mathcal{R} on high-dimensional space when adding a reconstruction loss on the output.

Performing reconstruction loss on the output of the model regardless of [reg] token can force the model to maintain the information and the attention map \mathcal{A} can be seen as a high-dimensional projected version of \mathcal{R} . In this way, the attention maps are constrained.

IV. EXPERIMENTS

A. Datasets

We train and test the proposed model using simulated data, which was generated with multiple adjustable parameters including signal-to-noise ratio (SNR), number of signal sources (K), number of snapshots (N), coherence, and broadband characteristics. We set the number of array elements $M = 10$, frequency $f = 2$ MHz (only for narrowband signal), and the range of impinge angles from -60 to 60 degrees. Our basic setting for variable parameters is defined as SNR = 0 dB, $K = 2$, $N = 100$, narrowband signals, non-coherent sources, and without array errors. When generating the data, we vary one variable parameter at each time while keeping the others fixed to explore the adaptability to different parameters of the model. Subsequently, we examine complex scenarios where multiple variable parameters are changed simultaneously. Each scenario above consist of a training set with 10000 samples and a testing set with 2000 samples. Each sample is composed

of an array-received signal \mathbf{X} and the corresponding DOA, where \mathbf{X} serves as the input to the model and DOA is used as the groundtruth. After training and testing the model with simulated data, we further evaluate its applicability by testing it with real-world data, which consists of single-frequency signals with a frequency of 30 KHz, snapshots $N = 512$, SNR= 5 dB, number of array elements $M = 5$, and a uniform circular array. There are 20 samples in this real-world dataset in total.

B. Benchmarking

We reimplement several model-based methods and recent state-of-the-art (SOTA) DL-based methods for comprehensive comparisons. The model-based methods are tested with meticulous parameter tuning, while the DL-based methods are trained with full convergence. The model-based methods contain MUSIC [50], ESPRIT [12], Root-MUSIC (R-MUSIC) [51], Spatial Smoothing-MUSIC (SPS-MUSIC) [52], Spatial Smoothing-Root-MUSIC (SPS-R-MUSIC) [52], and Spatial Smoothing-ESPRIT (SPS-ESPRIT) [52], BroadBand-MUSIC (BB-MUSIC) [21]. The DL-based methods include SubspaceNet [41] and DOA-Autoencoder [40].

We compare our methods with MUSIC, R-MUSIC, ESPRIT, DOA-AutoEncoder, and SubspaceNet under non-coherent and narrowband circumstances. Switching to the coherent scenario, we add these conventional methods with the SPS technique for fair comparisons. When the signal is broadband, BB-MUSIC especially designed for the broadband signal is compared.

C. Implementation Details

The base channel number of our model is empirically set to 128 and the number of stacked Transformer layers L is set to 1. We conduct experiments with varying channel numbers and observed that it has minimal impact on the results. We choose the AdamW [53] optimizer and set the learning rate to $1e^{-4}$. The conventional methods are implemented in Python and tested several times to ensure numerical stability.

We implement our proposed model on a workstation with an Intel 12-th i9 CPU and two Nvidia 3090 GPUs. For every group of experiments, the training stage costs around 20 minutes on 10000 simulated samples and the test stage cost only 5 seconds on 2000 simulated samples.

D. Main Results

1) *Adaptation of Various SNR*: In this section, we evaluate the adaptation of the proposed model against different SNRs. Since the focus is only on the adaptation of the proposed model to varying SNR, we keep parameters except for SNR constant across different experimental groups. The SNR values are sequentially set as -15 dB, -10 dB, -5 dB, 0 dB, and 5 dB. We pay particular attention to the performances of the model under challenging conditions since traditional methods have already demonstrated accurate and effective DOA estimation at high SNR.

The experimental results are shown in Fig. 2. From the observations, we can see that traditional subspace-based methods

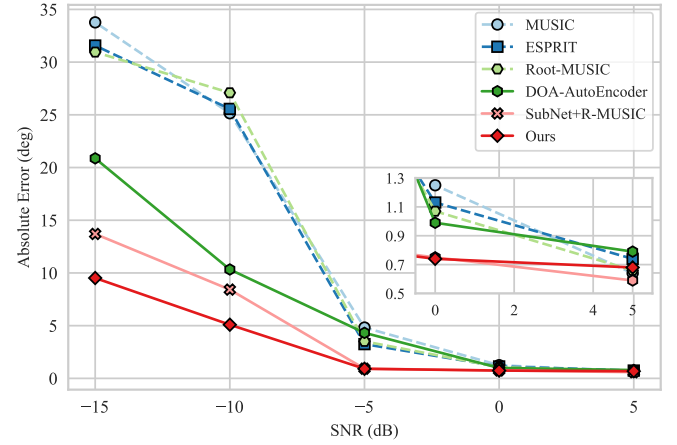


Fig. 2: DOA estimation under different SNRs (non-coherent, narrow band, without array errors, $N = 100$, $K = 2$).

exhibit excellent performances when SNR is relatively high. This is because subspace decomposition methods rely on the processing of the covariance matrix of the received signals. When SNR is high, the boundary between the signal subspace and the noise subspace becomes clear. Subspace methods are able to effectively suppress the influence of the noise subspace, resulting in improved performance. On the other hand, when SNR is low, traditional methods perform worse compared to DL-based methods, since DL-based methods do not rely on specific prior and instead learn complex mappings from raw data, which makes DL-based methods have greater adaptability to low SNR. It can be observed that our proposed method outperforms the other two DL-based methods under low SNR conditions, demonstrating that our proposed sensor-based attention mechanism is effective in this problem.

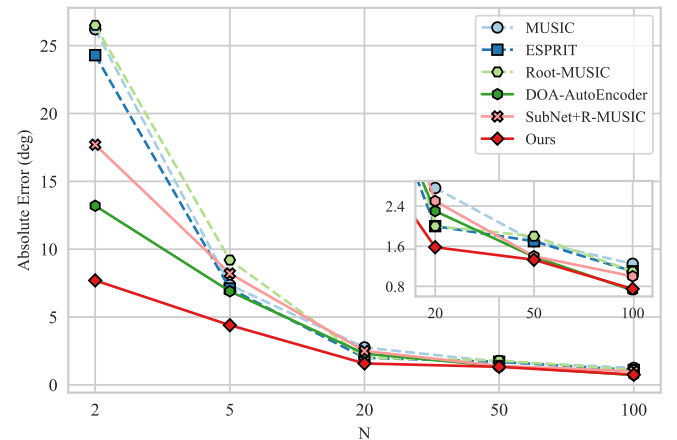


Fig. 3: DOA estimation under different numbers of snapshots (SNR= 0 dB, non-coherent, narrow band, without array errors).

2) *Adaptation of Various Number of Sources*: In this section, we evaluate the performance of the proposed model under different numbers of sources. We conduct a total of four groups of experiments, where each group keeps the parameters as

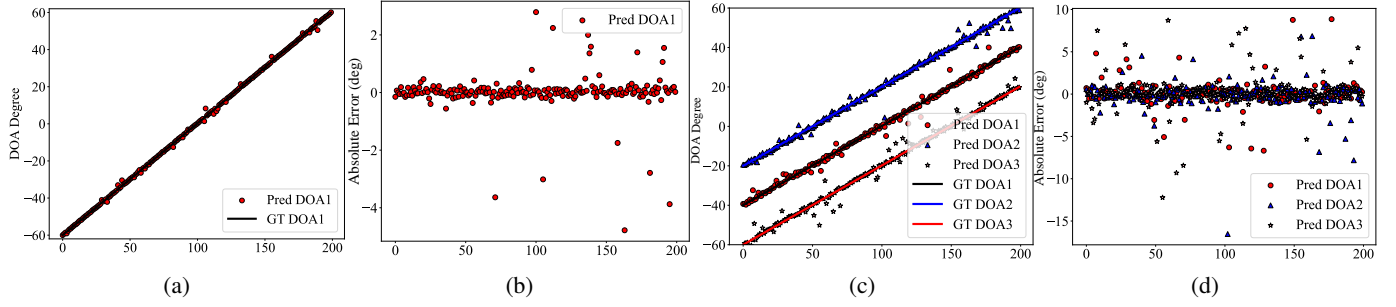


Fig. 4: DOA estimation with well trained deep Transformer model under $K = 1$ and 3 scenarios. (a) is the predicted DOA and the groundtruth DOA under the $K = 1$ setting, (b) is the absolute errors under the $K = 1$ setting. (c) is the predicted DOA and the groundtruth DOA under the $K = 3$ setting, (d) is the absolute errors under the $K = 3$ setting. “GT DOA” denotes the groundtruth DOA and “Pred DOA” represents the predicted DOA estimated by the network.

TABLE II: Comparisons with some conventional methods and DL-based methods under different numbers of sources scenario. Performances are reported by absolute error (deg).

methods	$K = 1$	$K = 2$	$K = 3$	$K = 4$	$K = 5$
MUSIC	0.67	1.25	2.66	4.98	6.90
ESPRIT	0.58	1.13	2.77	4.71	5.16
Root-MUSIC	0.57	1.07	2.41	3.19	4.90
DOA-AutoEncoder	0.62	0.97	2.09	2.76	4.05
SubNet+R-MUSIC	0.52	0.84	1.67	2.13	3.80
Ours	0.46	0.75	1.51	1.80	3.22

same as the basic setting, except for the number of sources. The number of sources, denoted as K , is sequentially set as 1, 2, 3, 4, and 5. In practical scenarios, super-resolution DOA estimation typically requires $M > K$ to ensure smooth subspace decomposition. In our experiments, we set the number of array elements, M , as 10. Theoretically, the possible number of sources ranges from 1 to 9, but for simplicity and focus on the main cases, we set the number of sources from 1 to 5.

The experimental results are shown in Tab. II. It can be observed that traditional methods often yield lower accuracy in handling multi-source problems under the poor condition of 0 dB. In contrast, the DOA-Autoencoder and Subspacenet methods outperform traditional methods, which can be attributed to the incorporation of deep modules that enable the model to learn multiple features globally rather than relying heavily on a single feature. Furthermore, the experimental results indicate that our proposed model exhibits the best adaptability to multi-source problems. The average absolute errors in the cases of 1, 2, 3, and 4 sources are 0.46, 0.75, 1.51, and 1.80 degrees, respectively, which again highlights the strong adaptability of our model to multi-source problems. In order to visually examine the performance of our model, we conducted angle scanning tests for two scenarios: $K = 1$ and $K = 3$. Fig. 4(a) and Fig. 4(b) represent the prediction results and errors of our model for the $K = 1$ scenario, where the angle scanning range for a single source is set from -60 to 60 degrees. Fig. 4(c) and Fig. 4(d) represent the prediction results and errors of our model for the $K = 3$ scenario, where we set a constant angular separation of 20 degrees between each source. It can be observed that the overall errors roughly align with the results

presented in Tab. II, which also validates the effectiveness of the proposed sensor-based attention mechanism in addressing this problem.

3) *Adaptation of Various Snapshots*: In this section, we explore the impact of different snapshot numbers N on the DOA estimation performance. To assess the adaptability of the proposed model to snapshot numbers, we conduct four groups of experiments where parameters, except for the snapshot number, remained constant. The snapshot numbers are sequentially set as 100, 50, 20, 5, and 2.

The experimental results are shown in Fig. 3. When the number of snapshots is high, traditional methods exhibit excellent performance, which is due to the increased time-domain resolution provided by a high number of snapshots. However, when the number of snapshots is low, DL-based methods demonstrate good adaptability. As the snapshot number decreases from 10 to 2, the performance of traditional methods sharply declines. This is due to the inability of temporal averaging of the covariance matrix to accurately replace sample averaging in low snapshot scenarios. The Subspacenet method, which relies on recovering the covariance matrix, also performs poorly in low snapshot numbers because of this limitation. Our method demonstrates the best performance in low snapshot conditions, which further confirms the effectiveness of the sensor-based attention mechanism.

4) *Adaptation of Coherency*: In this section, we explore the impact of signal coherency on the DOA estimation performance. Traditional subspace methods experience a decline in estimation performance when there is coherence among the sources, as the rank of the covariance matrix decreases, making spatial decomposition infeasible. In order to demonstrate the ability of the proposed model to handle coherent signals, we conduct a total of four major groups, each consisting of 16 subgroups of experiments. In each major group, the number of snapshots is set to 50, 20, 5, and 2, respectively. Within each major group, the SNR values are sequentially set to -5 dB, -3 dB, 0 dB, and 5 dB, while the remaining parameters are kept the same as the basic setting.

The experimental results are shown in Fig. 5. It can be observed that the MUSIC, ESPRIT, and R-MUSIC methods exhibit large errors during coherence periods, which can be attributed to the reduction in the rank of the covariance

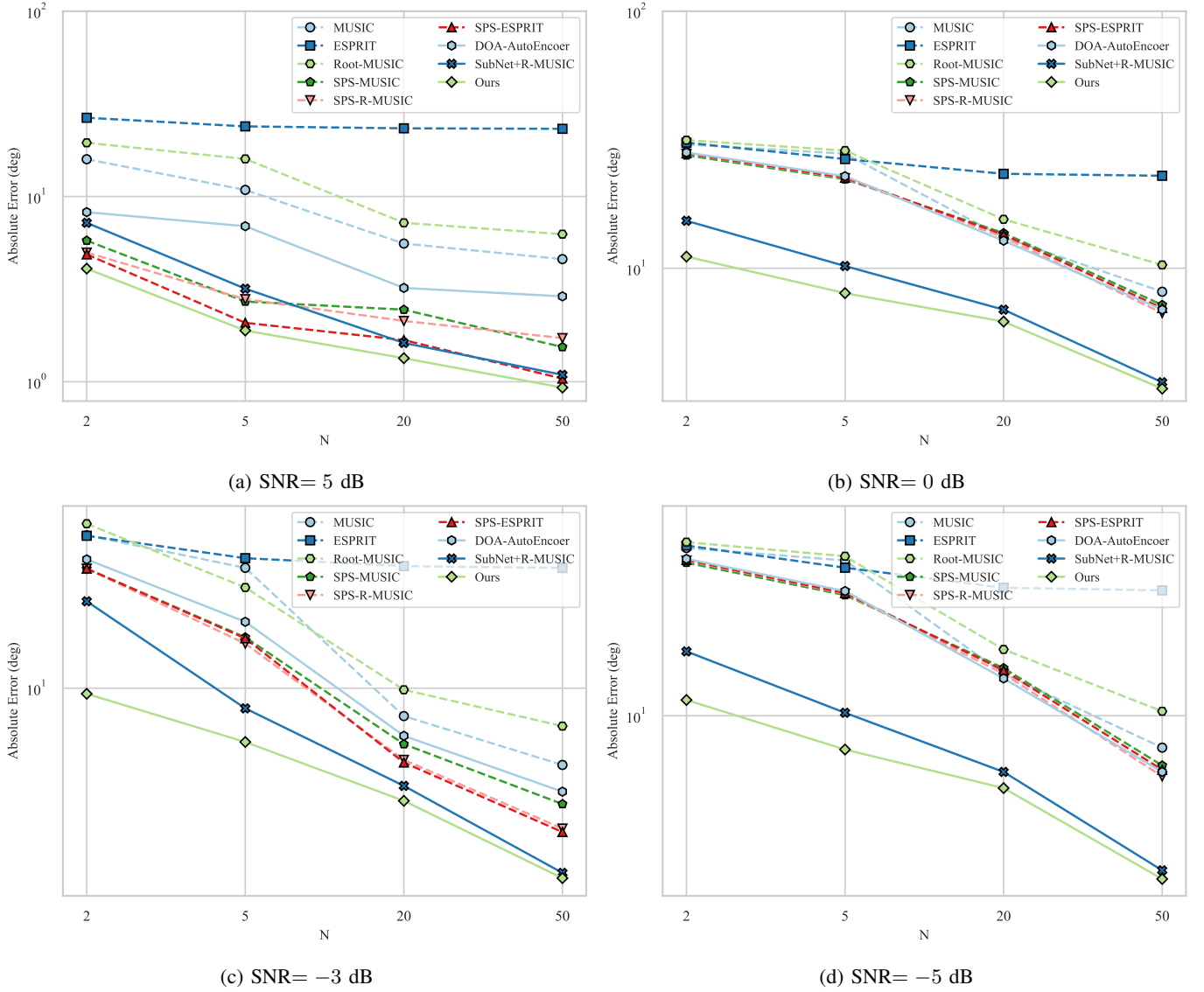


Fig. 5: Comparisons with other methods under the coherent-source scenario. Conventional methods are presented in dash lines, while DL-based methods are plotted in solid lines.

matrix. The SPS-MUSIC, SPS-ESPRIT, and SPS-R-MUSIC methods perform on par with the DL-based methods in terms of performance at high snapshot numbers and high SNR. However, our proposed model demonstrates superior performance at low SNR or low snapshot numbers. This demonstrates that the sensor-based attention mechanism proposed in our study possesses excellent processing capabilities for coherent signals.

5) Adaptation of Array errors: In this section, we investigate the impact of array errors on the DOA estimation performance. The array errors consider include mutual coupling errors, channel gain/phase inconsistencies errors, element position errors, and directional diagram errors. Accurately modeling these errors can be challenging, therefore, we adopt a simplified representation of the errors based on the approach proposed in [40]. The mutual coupling errors vector

is represented as follows,

$$\mathbf{c}_{err} = \alpha \times [c_1, c_2, \dots, c_M]^T, \quad (46)$$

where c_i is a complex number with amplitude ranging from 0.8 to 1 and phase ranging from -30 to 30 degrees. The specific values can be chosen during the experiments. α is the errors strength coefficient, which controls the severity of the errors. Similarly, the gain/phase inconsistencies errors matrix is formulated as follows,

$$\mathbf{L}_{err} = \alpha \times \text{diag}[l_1, l_2, \dots, l_M], \quad (47)$$

where l_i is a complex number with amplitude ranging from 0.8 to 1 and phase ranging from -30 to 30 degrees. The specific values can be chosen during the experiments. The element position errors vector is formed as follows,

$$\mathbf{b}_{err} = \alpha \times [b_1, b_2, \dots, b_M]^T \times d, \quad (48)$$

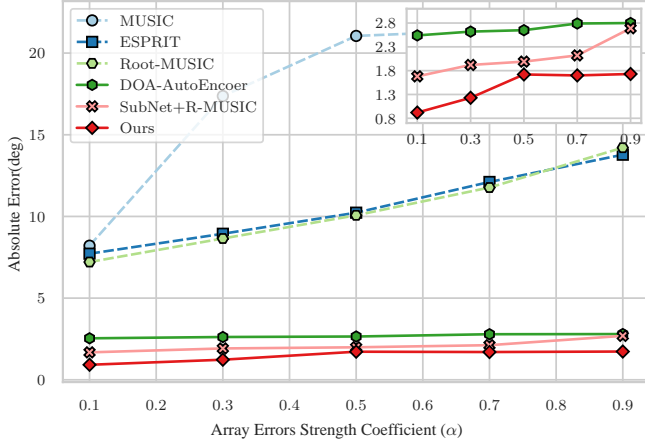


Fig. 6: DOA estimation under different array errors strength coefficients α (SNR= 0 dB, non-coherent, narrow band, and $N = 100$).

where $b_i \sim \mathcal{U}(-\alpha, \alpha)$. The directional diagram errors vector can be denoted as,

$$\mathbf{p}_{err} = \alpha \times [p_1, p_2, \dots, p_M]^T, \quad (49)$$

where p_i is a complex number with amplitude ranging from 0.8 to 1 and phase ranging from -30 to 30 degrees. The specific values can be chosen during the experiments. We believe these simplified approaches are reasonable because the deep model does not utilize any prior information about array errors.

Then, we sequentially set α from 0.1 to 0.9 to explore the adaptability of the model to array errors. The experimental results are shown in Fig. 6. It can be observed that as α increases, the estimation errors of traditional methods exhibit a noticeable upward trend. On the other hand, the errors of the DL-based methods do not show significant changes with increasing α . This is because the deep model does not rely on any array-specific prior assumptions, making it robust to various array errors. Our proposed model achieves the best performance, which further confirms the effectiveness of the sensor-based attention mechanism.

6) *Adaptation of Broadband*: In this section, we consider the performance of the model on broadband signals. The modeling of broadband signals is based on the approach proposed in [41], which can be represented as follows,

$$s_k(t) = \frac{1}{L} \sum_{l=0}^{L-1} s_{k,l} e^{2\pi j l \frac{B_f}{L f_s} t}, \quad (50)$$

where L represents the number of subcarriers, $s_{k,l}$ represents the l -th subcarrier of the k -th signal, which is independently modulated with a zero-mean complex Gaussian distribution with unit variance. f_s represents the sampling frequency and B_f means the signal bandwidth. In the experiments, we set $L = 500$, $f_s = 500\text{Hz}$, $B_f = 500\text{Hz}$, and the snapshot numbers are sequentially set to 500, 200, 50, and 20. The remaining parameters were kept the same as the basic setting.

The experimental results are shown in Fig. 7. We compare the traditional subspace methods, MUSIC, ESPRIT, and R-MUSIC, with the BB-MUSIC method for broadband sources, as well as the three DL-based methods. It can be seen that the performance of the BB-MUSIC algorithm is relatively good at high snapshot numbers. However, as the snapshot numbers decrease, the limitations of traditional methods become apparent. This is because BB-MUSIC requires decomposing the broadband signal into several narrowband signals. When the snapshot number is low, the sampled data does not contain sufficient frequency domain information, resulting in information loss and a decrease in DOA performance. In contrast, DL-based models significantly exhibit high performance on broadband signal estimation, particularly in low snapshot environments. We can see that our proposed model performs best in this problem which stems from the careful design of our model structure for this specific problem, including the sensor-based attention mechanism for joint feature extraction.

E. Ablation Study

1) *Sensor-based Attention*: We conduct the ablation study on our proposed sensor-based attention by implementing three variant models on the baseline. All variant models are trained to the convergence. The three variant models are listed as follows,

- 1) Only traditional spatial attention (i.e., only \mathcal{A}_S),
- 2) Only real-part attention (i.e., only \mathcal{A}_R),
- 3) Only imaginary-part attention (i.e., only \mathcal{A}_I),
- 4) Our proposed model.

TABLE III: Ablation study on our proposed sensor-based attention. \checkmark denotes that the corresponding attention is employed. The data in the table represents the absolute error.

\mathcal{A}_S	\mathcal{A}_R	\mathcal{A}_I	$K = 1$	$K = 2$	$K = 3$	$K = 4$	$K = 5$
\checkmark			1.26	1.59	2.43	2.88	5.46
	\checkmark		0.82	1.21	1.93	2.29	3.80
		\checkmark	0.55	0.88	1.82	2.01	3.52
	\checkmark	\checkmark	0.46	0.75	1.51	1.80	3.22

The ablation results are reported in Tab. III-C. It's clear to see that using traditional spatial attention would harm the estimation and only using \mathcal{A}_R or using \mathcal{A}_I would cause performance degradation. Using spatial attention \mathcal{A}_S can not model the covariance matrix \mathcal{R} and benefit from its task-related property. Moreover, only performing one of the real-part \mathcal{A}_R or imaginary-part \mathcal{A}_I attention cannot estimate DOA well. By using the proposed sensor-based attention, the model can achieve state-of-the-art (SOTA) performance.

2) *High Dimensional Bound of Attention*: In Sec. III-D, we discuss the attention map (i.e., \mathcal{A}_R and \mathcal{A}_I) should be bounded in high dimension to ensure the lossless information of the signal covariance matrix. We choose to add an auxiliary reconstruction loss to restrict the attention map in high-dimensional feature space. To verify the effectiveness of the restriction, we design the ablation model without using the reconstruction loss. After training it on the basic setting, we find that the performance without reconstruction loss is

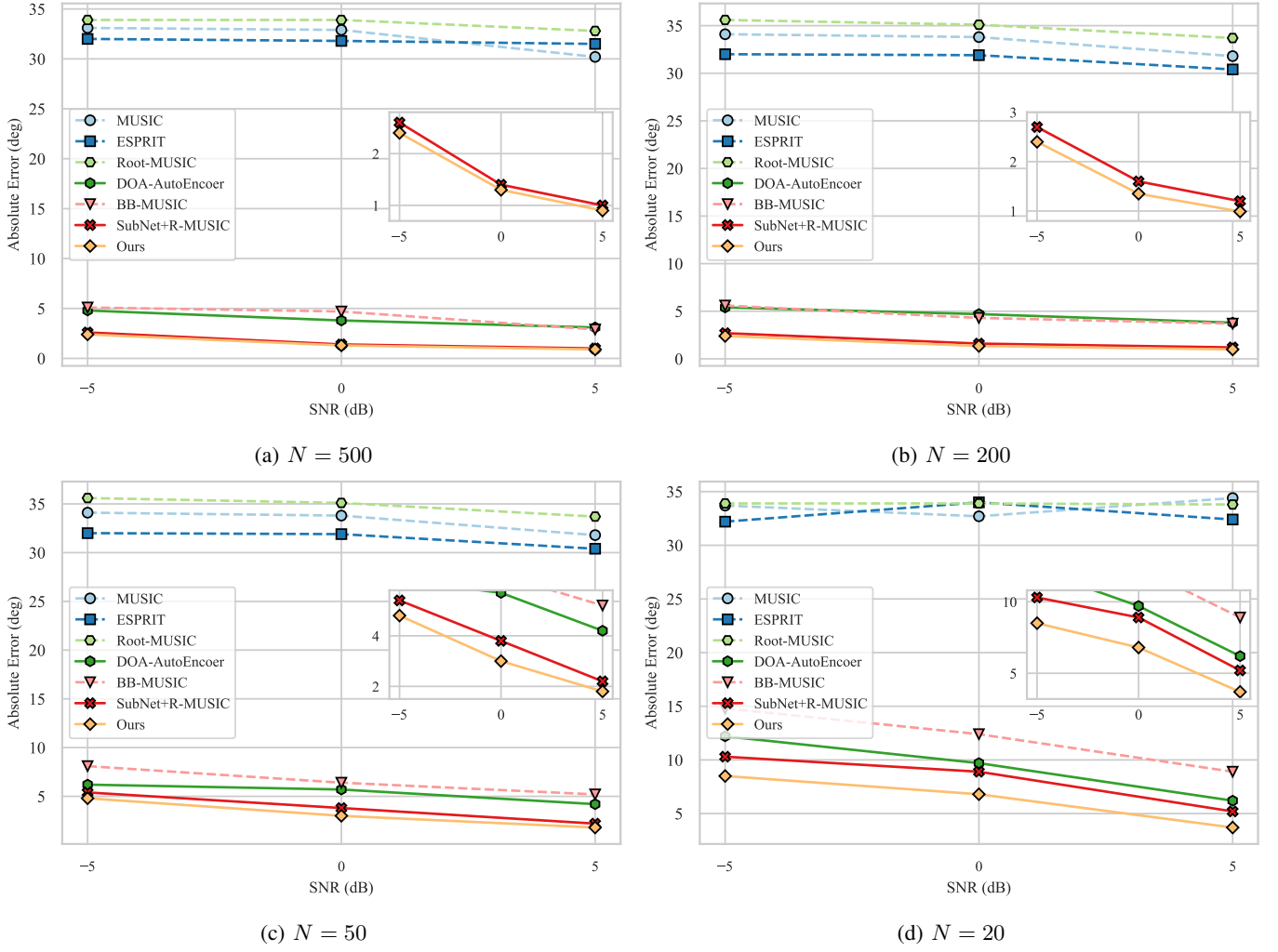


Fig. 7: Comparisons with other methods under the broadband-source scenario. Conventional methods are presented in dash lines, while DL-based methods are plotted in solid lines.

degraded. The absolute error rises from 0.75 to 0.89, which shows that the high-dimensional bound is necessary.

F. Discussion

1) *Complex Situation*: This section explores the adaptability of models to various complex situations. The signals in real-world scenarios can be complex and influenced by various factors. Therefore, it is necessary to simultaneously consider the various situations discussed in Sec. IV.

In this section, we conducted a total of six groups of experiments to explore the adaptability of the model to complex situations. In these groups, we gradually make the experimental conditions more challenging while keeping the number of snapshots constant, because the number of snapshots is often controllable even in complex situations. The experimental setup and results are shown in Tab. IV. From the comparison of the first and second rows, we can see that the introduction of broadband signals leads to the degradation of model performance. This is because broadband signals contain more complex frequency domain information, which may pose learning difficulties for the model with a limited

number of snapshots. From the comparison of the second and third rows, we can see that increasing array errors leads to degradation in model performance, but the impact is not significant. This is consistent with the analysis in Sec IV, as deep models do not rely on prior information about the array errors during the learning process. From the comparison of the third and fourth rows, we can observe that decreasing the SNR results in a decrease in model performance. We conducted a dedicated analysis on this aspect in Sec IV. From the comparison of the fourth and fifth rows, it can be seen that increasing the number of signal sources leads to a rapid decline in model performance. Going from $K = 2$ to $K = 3$ nearly doubles the absolute estimation error of the model. The sixth row represents a set of extreme conditions that we set as a control. Under these conditions, the model's estimation error reaches 5.56 degrees, which shows that our model has great adaptability to complex scenarios.

2) *Real World Signal*: In this section, we validate the proposed model on real-world data. Since the array structure of the real-world data is a uniform circular array, we first generate simulated data with a uniform circular array configuration for

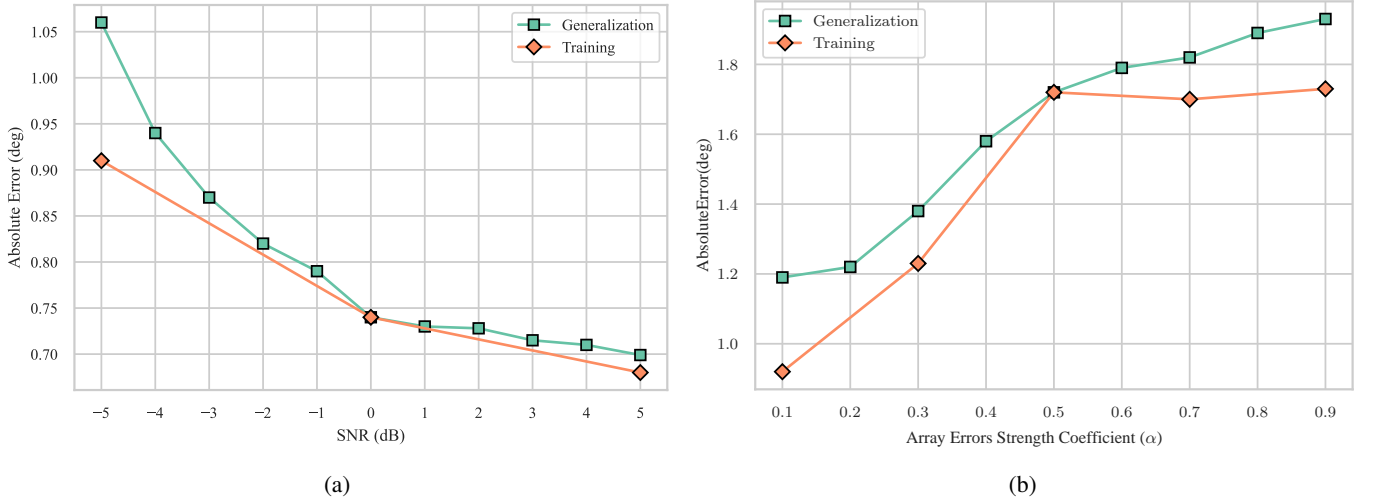


Fig. 8: Generalization ability of our proposed method. (a) denotes that model is trained on SNR= 0 dB and tested on different SNRs. (b) represents that the model is trained on $\alpha = 0.5$ and tested on different α .

TABLE IV: Performances of our proposed Transformer under extremely complex scenarios.

SNR	Snapshots	Array errors	Coherent	Broadband	Number sources	Abs. Error (deg)
5 dB	$N = 500$	$\alpha = 0.1$	✓		$K = 2$	0.32
5 dB	$N = 500$	$\alpha = 0.1$	✓	✓	$K = 2$	1.03
5 dB	$N = 500$	$\alpha = 0.3$	✓	✓	$K = 2$	1.16
0 dB	$N = 500$	$\alpha = 0.3$	✓	✓	$K = 2$	1.49
0 dB	$N = 500$	$\alpha = 0.3$	✓	✓	$K = 3$	2.82
0 dB	$N = 500$	$\alpha = 0.5$	✓	✓	$K = 5$	5.56

TABLE V: Comparisons between our method and a widely-used conventional algorithm MUSIC on the real-world dataset which obtains samples with SNR= 0 dB.

methods	DOA degree				
	-60	-30	0	30	60
MUSIC	2.00	1.20	3.50	0.67	22.0
Ours	1.37	0.83	1.52	0.43	1.31

training the model. Subsequently, we perform transfer learning by using 15 samples from the real-world data as the training set, while the remaining 5 samples are used for testing. The results are shown in Tab. V. It can be observed that our method demonstrates more stable performance on real-world data compared to MUSIC. This indicates that our method exhibits stronger adaptability to variations and noise in the real world, enabling more accurate DOA estimation. Traditional methods may be more susceptible to disturbances from non-ideal factors when dealing with real-world data, leading to less stable and accurate estimation results. However, our proposed method overcomes these challenges, enhancing the robustness and accuracy of DOA estimation.

3) *Generalization Ability for Unseen Scenario*: In this section, we conduct generalization tests on the proposed method to explore how the model can extend its learning outcomes to scenarios not included in the training dataset. This experiment is necessary because, in practical applications, it is often impossible to precisely model complex scenarios, which inevitably leads to the operation of the model in new

environments. Two groups of experiments are conducted to investigate the model's generalization ability concerning SNR and array errors, respectively. For the former, we trained the model only with an SNR of 0 dB and performs generalization tests on SNR ranging from -5 dB to 5 dB. For the latter, we trained the model with $\alpha = 0.5$ and conducted generalization tests with α ranging from 0.1 to 0.9.

The experimental results are shown in Fig. 8. From Fig. 8(a), we can see that the performance degradation rate at which the absolute error decreases with increasing SNR is smaller than the rate at which the absolute error increases with decreasing SNR. This is because, at lower SNR, the model not only experiences difficulties in learning due to the low SNR itself, but generalization also introduces more errors. Similar conclusions can be drawn from Fig. 8(b), where the performance degradation rate at which the absolute error increases with increasing array errors intensity is greater than the rate at which the absolute error decreases with decreasing array errors intensity. These two groups of experiments demonstrate that our model has a certain level of generalization ability and can handle variations in scenarios. Although its direct generalization performance is not as good as the performance achieved when tested under the same conditions as training, overall, its performance is still satisfactory.

4) *Blind Number of Sources*: In practical DOA estimation, the number of signal sources may not be known, while our model requires information about the number of sources for application. Therefore, in this section, we propose a framework for estimating the number of signal sources to assist our DOA

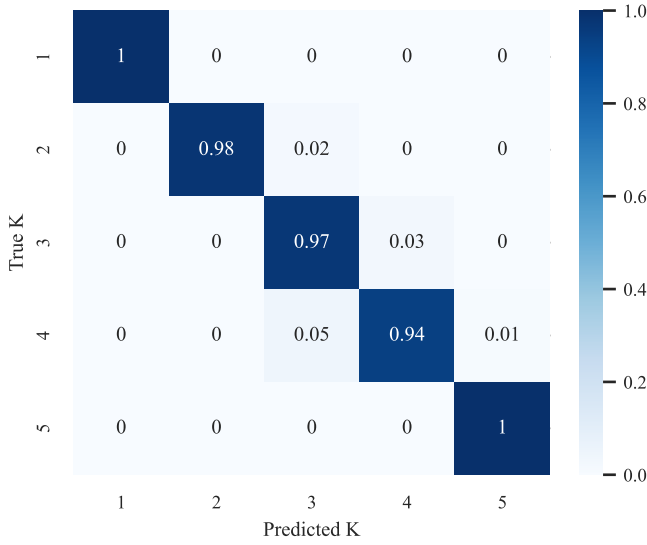


Fig. 9: Confusion matrix of proposed classification network.(SNR= 0 dB, $N = 100$, non-coherent, narrow band, and without array errors)

estimation model. We utilize the same model architecture as the DOA estimation framework for handling the source number estimation problem, with the only difference being the replacement of the regression head in the model's backend with a classification head and a reduction in the number of Transformer layers.

The experimental setup is the same as the basic setting, and the resulting confusion matrix is shown in Fig. 9. Each element m_{ij} in the confusion matrix represents the probability of predicting the number of true signal sources as i when the actual number of sources is j . Under the conditions of SNR 0 dB and 100 snapshots, such results are satisfactory because the problem that estimating the number of multiple sources in adverse environments is often challenging to solve. After estimating the number of sources, we can employ the corresponding trained regression model to estimate the DOA in a cascade manner.

V. CONCLUSION

In this paper, we propose a novel Transformer model to solve the DOA estimation problem. Our method enhances the original Transformer method by introducing a sensor-based attention mechanism specially designed for DOA estimation. These changes allow the model to be guided to learn to a certain extent and pay more attention to the information that is really useful for DOA estimation, which is proven to be effective in DOA estimation tasks. The working principles of these changes are mathematically derivable, thus providing a degree of interpretability to our model. Compared to traditional methods and other DL-based approaches, our proposed method demonstrates superior performance. It is capable of handling scenarios with a low SNR, a limited number of snapshots, multiple signal sources, coherent sources, broadband sources, and array errors. It also exhibits excellent adaptability to extremely

complex scenarios and unknown scenarios. These abilities show that our method has strong practicality compared with traditional methods and good interpretability compared with previous DL-based methods.

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