

Article

Blind SINR Estimation Algorithm Based on Joint Eigenvalue-Steering Vector Decoupling in Non-Cooperative Interference

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Abstract

To address the limitations of traditional Signal-to-Interference-plus-Noise Ratio (SINR) estimation methods under non-cooperative malicious interference, such as their confinement to specific modulation signals and the narrow effective estimation range of Signal-to-Noise Ratio (SNR), this paper proposes an adaptive robust SINR estimation algorithm based on joint decoupling of eigenvalues and steering vectors. The algorithm first realizes the joint estimation of the number of sources and noise power under finite snapshots via Marchenko-Pastur (MP) law-based iteration, then completes the coarse estimation of desired signal power through steering vector-eigenvector matching and performs strategy switching according to the coarsely estimated Signal-to-Interference Ratio (SIR). In scenarios where the desired signal power is non-dominant, the robust Capon method with adaptive diagonal loading is adopted for fine estimation, and, finally, the interference power is decoupled using the matrix trace identity. The algorithm is independent of modulation characteristics, applicable to both constant-modulus and non-constant-modulus signals, and only requires prior information of the Direction of Arrival (DOA) of the desired signal. Simulation results demonstrate that under complex non-ideal conditions, including 30 dB Interference-to-Noise Ratio (INR), steering vector mismatch, and finite snapshots, the average Root Mean Square Error (RMSE) of the proposed algorithm across the entire SNR range is only 0.83 dB, which significantly outperforms mainstream blind estimation algorithms such as RMT-BSE, M2M4, and SSME. Its robustness and universality are more in line with the requirements of non-cooperative anti-jamming communications.

Keywords: SINR estimation; Capon spectrum; steering vector mismatch; adaptive diagonal loading; eigen subspace; source number estimation

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1. Introduction

In the context of modern information-centric confrontation, the electromagnetic spectrum has become a strategic resource determining communication link reliability. Adaptive frequency selection, a key enabler of dynamic spectrum access and active anti-jamming, is widely applied in cognitive radio, tactical communication, and similar systems. Its core principle is real-time channel quality assessment across candidate frequency

points, followed by dynamic switching to the optimal channel. The reliability of this decision-making process directly depends on the accuracy of channel quality metrics. As a core parameter for quantifying channel quality, the Signal-to-Interference-plus-Noise Ratio (SINR) directly underpins frequency selection decisions. Consequently, high-precision SINR estimation is a prerequisite for realizing active anti-jamming communications.

In recent years, AI-native solutions for dynamic spectrum management have also attracted extensive attention. Emerging multi-agent reinforcement learning (MARL)-based MAC protocol emergence frameworks enable communication nodes to autonomously learn spectrum access coordination strategies through interactions without pre-defined protocol rules, providing a new technical route for dynamic spectrum access in non-cooperative and uncertain environments [1]. Nevertheless, both traditional adaptive frequency selection architectures and emerging intelligent spectrum access protocols rely on accurate channel state perception at the physical layer, and their effective operation is fundamentally underpinned by reliable estimation of core channel quality metrics such as SINR.

In non-cooperative interference scenarios, the jamming environment has three distinct characteristics: (1) the jammer's modulation scheme, coding type, transmit power and behavioral strategies are all unknown, making it impossible for the receiver to establish a reliable reference model; (2) the jammer may deliberately mimic the modulation features, bandwidth, statistical distribution or even symbol rate of the desired signal, resulting in unpredictable behavior; (3) jamming and desired signals are fully aliased in both time and frequency domains, and the jammer often overwhelms the desired signal via power superiority, rendering traditional time-frequency filtering ineffective. In this context, the core challenge of SINR estimation lies in blindly separating and accurately decoupling desired signal and interference power components from the received signal, given their full time-frequency coupling and no prior jammer information.

To achieve accurate SINR estimation, researchers worldwide have conducted extensive studies from diverse technical perspectives. According to reliance on prior information, existing SINR estimation methods fall into three categories: non-blind estimation, fully blind estimation, and semi-blind estimation [2]. Non-blind methods rely on known reference information inserted at the transmitter, such as pilots, training sequences, or silent periods, with typical examples including maximum likelihood estimators [3–5] and decision feedback methods [6]. While they achieve high estimation accuracy in cooperative scenarios, they face fundamental limitations in non-cooperative environments: pilots and training sequences occupy spectral resources and reduce transmission efficiency; no schedulable silent periods exist under continuous jamming; and the receiver cannot pre-negotiate reference signal formats with the transmitter. These limitations make non-blind methods entirely impractical for non-cooperative anti-jamming communications.

Semi-blind estimation methods balance minimal prior information with blind statistical processing, such as iterative estimators combining sparse pilots with decision feedback, Turbo estimation architectures based on decoding soft information [7–9], and recent data-driven approaches that map SINR values from statistical features of received signals [10–12]. However, they also struggle to adapt to non-cooperative scenarios: sparse pilots lead to significant channel estimation errors under strong interference, while decision feedback causes severe error propagation; machine learning methods have generalization capability strictly limited by the interference types covered in training data, and their non-linear mapping relationships completely fail when faced with unknown jamming patterns.

Fully blind estimation methods require no reference signals and rely solely on the statistical or structural properties of received signals to achieve power decoupling. Among these, moment-based methods exploit differences in second- and fourth-order cumulants between signals and Gaussian noise, with typical representatives including the

M2M4 estimator [13], the Split Symbol Moments Estimator (SSME) [14,15], and the Standard Normal Variate (SNV) estimator [16]; empirical characteristic function methods jointly estimate signal and noise parameters by fitting the discrepancy between empirical and theoretical characteristic functions [17,18]; spectrum segmentation methods achieve power decoupling via differences in frequency-domain energy distribution [19]; eigenvalue decomposition (EVD) methods decompose the sample covariance matrix and infer signal and noise powers directly from eigenvalue distributions [20].

However, in non-cooperative interference scenarios, most fully blind methods degrade significantly. The M2M4 estimator, which relies on the constant modulus property, misclassifies constant-modulus interference power as desired signal power, leading to large estimation errors. The SSME requires precise symbol timing to split symbols, but interference components equally exist in both halves when the jammer shares the same symbol rate, resulting in severely overestimated SINR. The SNV estimator only applies to constant-modulus signals; when the jammer uses identical modulation, the amplitude variance of the received signal is significantly inflated, preventing signal-interference distinction. Spectrum segmentation methods assume the desired signal concentrates energy in specific narrow bands, but the energy separation boundary disappears when the jammer occupies the same bands, making complete separation impossible.

In summary, the EVD method based on the received signal covariance matrix is currently the only viable technical approach for non-cooperative interference scenarios. It requires no assumptions about time-domain waveform, spectral shape, or higher-order statistics of the signal, and leverages the physical difference in spatial arrival angles between the desired signal and interference to achieve power separation. With clear physical interpretation and broad applicability, it can theoretically accommodate signals of any modulation type, which aligns well with the core requirement of non-cooperative scenarios: no prior information about either the signal or the jammer. Nevertheless, traditional eigen-decomposition-based blind estimation methods have two critical flaws: (1) when desired signal and interference powers are comparable, eigenvalues in the signal subspace become strongly coupled, making it impossible to distinguish individual power components by eigenvalue magnitude alone, thus introducing fundamental estimation bias; (2) conventional eigenvalue classification criteria default to associating large eigenvalues with the desired signal and small ones with interference, but dynamically varying jammer power in non-cooperative scenarios makes such assignments unpredictable, leading to frequent misclassifications.

To address these flaws, this paper proposes a blind SINR estimation algorithm based on joint eigenvalue-steering vector decoupling. This approach breaks through the limitation of traditional eigen-decomposition methods that rely solely on eigenvalue magnitudes for power separation by combining eigenvalue statistical properties with spatial prior information of steering vectors. Specifically, it locates the eigen component corresponding to the desired signal via the matching relationship between steering vectors and eigenvectors, then achieves power decoupling between the desired signal and interference using robust spatial filtering, thereby resolving the estimation bias caused by eigenvalue coupling. Concretely, this paper constructs a progressive SINR estimation framework of coarse feature subspace estimation plus robust Capon refinement: (1) first, the Marchenko-Pastur (MP) law is used for joint estimation of source number and noise power under limited snapshots; (2) a coarse estimate of desired signal power is obtained via correlation coefficient matching between steering vector and eigenvectors, followed by strategy switching based on the coarsely estimated signal-to-interference ratio (SIR); (3) when the desired signal is not power-dominant, a fully scenario-adaptive closed-form solution for diagonal loading is derived to suppress signal self-cancellation, and fine estimation is performed using Capon spatial spectrum estimation; (4) finally, interference

power is decoupled using matrix trace identities, and SINR is calculated in a closed-loop manner. The algorithm only requires prior knowledge of the desired signal's direction of arrival (DOA), no prior jammer information, and is independent of signal modulation characteristics, making it universally applicable to both constant-modulus and non-constant-modulus signals. Simulation results show that the proposed algorithm achieves high-precision SINR estimation under harsh conditions where multiple non-ideal factors (strong interference, limited snapshots, steering vector mismatch) coexist.

The main innovations and advances of this paper are summarized as follows:

- (1) To address the poor accuracy and easy misjudgment of traditional source number estimation methods such as AIC, MDL, and GDE under finite snapshots and low SNR, an iterative joint estimation method for source number and noise power based on the MP law is proposed. It requires no manual threshold setting and can stably output estimation results under small snapshots and strong interference conditions, providing reliable a priori support for subsequent SINR estimation.
- (2) A progressive SINR estimation architecture of eigen subspace-based coarse estimation–robust Capon-based fine estimation is constructed. The desired signal component is located by matching correlation coefficients between the steering vector and eigenvectors, and a strategy-switching mechanism based on coarsely estimated SIR is designed. It directly outputs the coarse estimation result when the desired signal is dominant and enables robust fine estimation when it is non-dominant, solving the estimation bias caused by eigenvalue coupling in traditional EVD methods when signal and interference powers are close.
- (3) An optimal closed-form solution for adaptive diagonal loading under steering vector mismatch is derived, effectively suppressing the signal self-cancellation effect in Capon estimation. The algorithm achieves power decoupling solely based on the spatial DOA difference between desired signal and interference, independent of signal modulation type, and is universally applicable to both constant-modulus and non-constant-modulus signals. It remains stable even in scenarios where the jammer completely mimics the time-frequency or statistical characteristics of the desired signal.

The rest of this paper is organized as follows. Section 2 establishes the uniform linear array received signal model and reviews the fundamentals of array subspace theory and Capon spatial spectrum estimation. Section 3 elaborates on two key supporting technologies: the iterative source number and noise power joint estimation method based on the Marchenko-Pastur law, and the correlation theory between steering vectors and eigenvectors. Section 4 details the design of the proposed adaptive robust blind SINR estimation algorithm, including the progressive coarse-to-fine estimation framework, optimal adaptive diagonal loading strategy, and interference power decoupling procedure. Extensive simulation results and performance comparisons with mainstream algorithms are presented in Section 5. Finally, Section 6 concludes this paper and outlines future research directions.

Notation: For a general matrix X , X^H and X^T denote its conjugate transpose and transpose, respectively. For a square matrix Y , Y^{-1} denotes its inverse. $|\cdot|$ denotes the modulus of a complex number; $\|\cdot\|$ denotes the ℓ_2 -norm of a matrix. $\mathbb{E}[\cdot]$ denotes the expectation. I_M denotes the M -dimensional unit matrix.

2. Array Signal System Model

2.1. Uniform Linear Array Received Signal Model

This paper adopts a uniform linear array (ULA) consisting of M array elements with an inter-element spacing of $d = \lambda/2$, where λ denotes the wavelength of the carrier

signal. It is assumed that there exists one desired signal and Q far-field narrowband interference signals in space, all of which satisfy the far-field plane wave propagation assumption. The array-received signal at the k -th snapshot can be expressed as:

$$\mathbf{x}(k) = \mathbf{a}(\theta_0)s(k) + \sum_{q=1}^Q \mathbf{a}(\theta_q)j_q(k) + \mathbf{n}(k), \quad k=1,2,\dots,K. \quad (1)$$

where K denotes the total number of sampling snapshots; $s(k)$ represents the time-domain sampled complex envelope of the narrowband RF signal for the desired signal, which satisfies the wide-sense stationary (WSS) property, with its average power given by $\sigma_s^2 = \mathbb{E}[|s(k)|^2]$; $j_q(k)$ is the time-domain sampled complex envelope of the narrowband RF signal for the q -th interference signal, which is mutually independent of the desired signal and other interference signals, and its average power is $\sigma_{j,q}^2 = \mathbb{E}[|j_q(k)|^2]$; $\mathbf{n}(k) \in \mathbb{C}^{M \times 1}$ is the additive white Gaussian noise (AWGN) vector of the array receiving channels, where the noise across channels is independent and identically distributed (i.i.d.), and its covariance matrix is $\mathbb{E}[\mathbf{n}(k)\mathbf{n}(k)^H] = \sigma_n^2 \mathbf{I}_M$, where σ_n^2 is the average noise power per array element, and $\mathbf{I}_M$ is the M -dimensional identity matrix; θ_0 is the DOA of the desired signal, θ_q is the DOA of the q -th interference signal, and $\mathbf{a}(\theta)$ is the array steering vector corresponding to the incident angle θ . For a ULA, it can be expressed as:

$$\mathbf{a}(\theta) = [1, e^{-j2\pi d \sin \theta / \lambda}, \dots, e^{-j2\pi(M-1)d \sin \theta / \lambda}]^T. \quad (2)$$

The second-order statistical properties of the array-received signal are characterized by its covariance matrix, whose statistical expectation form is given by:

$$\mathbf{R} = \mathbb{E}[\mathbf{x}(k)\mathbf{x}(k)^H] = \mathbf{R}_s + \mathbf{R}_j + \mathbf{R}_n, \quad (3)$$

where $\mathbf{R}_s = \sigma_s^2 \mathbf{a}(\theta_0)\mathbf{a}(\theta_0)^H$ denotes the covariance matrix of the desired signal; $\mathbf{R}_j = \sum_{q=1}^Q \sigma_{j,q}^2 \mathbf{a}(\theta_q)\mathbf{a}(\theta_q)^H$ is the covariance matrix of the interference signals; and $\mathbf{R}_n = \sigma_n^2 \mathbf{I}_M$ represents the noise covariance matrix. In practical engineering applications, the sample covariance matrix can be computed from a finite number of snapshot data as follows:

$$\hat{\mathbf{R}} = \frac{1}{K} \sum_{k=1}^K \mathbf{x}(k)\mathbf{x}(k)^H. \quad (4)$$

As the number of snapshots $K \rightarrow \infty$, the sample covariance matrix $\hat{\mathbf{R}}$ converges in probability to the statistical covariance matrix $\mathbf{R}$.

2.2. Fundamentals of Array Covariance Matrix and Subspace Theory

The array covariance matrix $\mathbf{R}$ is an M -order Hermitian positive definite matrix, and it admits a unitary eigenvalue decomposition:

$$\mathbf{R} = \mathbf{U}\mathbf{\Lambda}\mathbf{U}^H = \sum_{m=1}^M \lambda_m \mathbf{u}_m \mathbf{u}_m^H, \quad (5)$$

where $\mathbf{\Lambda} = \text{diag}(\lambda_1, \lambda_2, \dots, \lambda_M)$ is the diagonal matrix of eigenvalues arranged in descending order, $\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_M$, and $\mathbf{U} = [\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_M]$ is the unitary eigenvector matrix corresponding to these eigenvalues, satisfying $\mathbf{U}^H \mathbf{U} = \mathbf{I}_M$, with $\mathbf{u}_m$ being the normalized eigenvector associated with eigenvalue λ_m . Let the total number of incident sources in the space be $D = Q + 1$. According to subspace theory, the eigenvalues of the covariance matrix can be divided into two categories:

- (a) Signal subspace: The first D largest eigenvalues, $\lambda_1 \geq \dots \geq \lambda_D > \sigma_n^2$, correspond to the eigenvector matrix $\mathbf{U}_s = [\mathbf{u}_1, \dots, \mathbf{u}_D]$, which spans the signal subspace. All steering vectors of the incident signals lie within this subspace.
- (b) Noise subspace: The subsequent $M - D$ smallest eigenvalues, $\lambda_{D+1} \approx \dots \approx \lambda_M \approx \sigma_n^2$, correspond to the eigenvector matrix $\mathbf{U}_n = [\mathbf{u}_{D+1}, \dots, \mathbf{u}_M]$, which spans the noise subspace. This subspace is orthogonal to the signal subspace, satisfying $\mathbf{U}_s^H \mathbf{U}_n = 0$.

Based on the matrix trace identity, the total received power of the array satisfies:

$$\text{tr}(\mathbf{R}) = \sum_{m=1}^M \lambda_m = M \left(\sigma_s^2 + \sum_{q=1}^Q \sigma_{j,q}^2 + \sigma_n^2 \right). \quad (6)$$

2.3. Capon Spatial Spectrum Estimation

The Capon spatial spectrum estimation constitutes the core theoretical foundation of the algorithm proposed in this paper. Its essence lies in realizing an unbiased estimation of the incident signal power from a specific spatial direction via constrained optimization. The core idea is that, for a given incident angle θ , the total power of interference and noise from all non-target directions is minimized under the constraint that the spatial response gain at the specified angle is strictly unity, such that the output power only contains the incident signal power from the desired direction. For the incident angle θ_0 of the desired signal, its corresponding steering vector is $\mathbf{a}(\theta_0)$. The constrained optimization problem of Capon spectrum estimation can be formulated as:

$$\begin{aligned} \min_{\mathbf{w}} \quad & \mathbf{w}^H \mathbf{R} \mathbf{w} \\ \text{s.t.} \quad & \mathbf{w}^H \mathbf{a}(\theta_0) = 1, \end{aligned} \quad (7)$$

where $\mathbf{w} \in \mathbb{C}^{M \times 1}$ denotes the weight vector of the spatial filter. By solving this optimization problem via the method of Lagrange multipliers, a closed-form solution for the optimal spatial filter weight vector is derived as:

$$\mathbf{w}_{\text{opt}} = \frac{\mathbf{R}^{-1} \mathbf{a}(\theta_0)}{\mathbf{a}^H(\theta_0) \mathbf{R}^{-1} \mathbf{a}(\theta_0)}. \quad (8)$$

Substituting the optimal weight vector into the output power expression yields the Capon spectral estimate corresponding to the incident angle θ_0 of the desired signal, which serves as the power estimate of the desired signal:

$$\hat{\sigma}_s^2 = \mathbf{w}_{\text{opt}}^H \mathbf{R} \mathbf{w}_{\text{opt}} = \frac{1}{\mathbf{a}(\theta_0)^H \mathbf{R}^{-1} \mathbf{a}(\theta_0)}. \quad (9)$$

2.4. Self-Cancellation of Desired Signals Under Steering Vector Mismatch

In practical engineering scenarios, non-ideal factors including array amplitude-phase errors, incident angle estimation deviations, and array element mutual coupling give rise to discrepancies between the prior steering vector actually employed by the algorithm and the true steering vector. This paper adopts the mainstream additive mismatch model to model the steering vector of the desired signal:

$$\hat{\mathbf{a}}(\theta_0) = \mathbf{a}(\theta_0) + \mathbf{e}, \quad (10)$$

where $\mathbf{a}(\theta_0)$ denotes the true steering vector of the desired signal, $\hat{\mathbf{a}}(\theta_0)$ represents the prior steering vector actually employed, and $\mathbf{e}$ is the mismatch error vector. The elements of $\mathbf{e}$ follow a complex Gaussian distribution $\mathbf{e} \sim \mathcal{CN}(0, \sigma_e^2 \mathbf{I}_M)$, where σ_e^2 stands for the variance of the mismatch error.

In the presence of steering vector mismatch, the constraint $\mathbf{w}^H \mathbf{a}(\theta_0) = 1$ no longer holds for the true desired signal. As such, the Capon optimization process treats the true

desired signal (which is mismatched with the prior steering vector) as interference for suppression, resulting in an underestimation of the desired signal power, a phenomenon referred to as signal self-cancellation. In high SNR scenarios, the desired signal dominates the covariance matrix. To meet the objective of minimizing output power, the Capon optimization forms nulls in the true direction of the desired signal, which drastically exacerbates the signal self-cancellation effect. Consequently, the estimation error of the desired signal power increases with increasing SNR.

3. Two Key Technologies for SINR Estimation

3.1. Source Number Estimation for Limited Snapshots Based on the MP Law

To address the limitations of traditional source number estimation methods such as AIC and MDL, which rely on asymptotic properties under large sample sizes and suffer significant performance degradation in scenarios with limited snapshots and low SNR, this paper proposes an iterative source number estimation method based on the MP law of random matrices. This method specifically models the statistical characteristics of eigenvalues of random matrices under limited snapshot conditions, eliminating the need for manual threshold setting and enabling joint unbiased estimation of both the number of sources and noise power.

3.1.1. Theoretical Foundation of the MP Law

Define the element-snapshot ratio $c = M/K$ as the core parameter of the MP Law. For scenarios with only spatial white Gaussian noise, the eigenvalues of the sample covariance matrix strictly follow the MP distribution, and the theoretical upper and lower bounds of their distribution are given by:

$$\begin{cases} \lambda_{\min}^{MP} = \sigma_n^2 (1 - \sqrt{c})^2 \\ \lambda_{\max}^{MP} = \sigma_n^2 (1 + \sqrt{c})^2 \end{cases}. \quad (11)$$

The core conclusion of the MP Law is as follows: In a pure noise scenario, all eigenvalues of the sample covariance matrix fall within the interval $[\lambda_{\min}^{MP}, \lambda_{\max}^{MP}]$; when directional incident sources exist in the spatial domain, their corresponding eigenvalues will exceed the statistical upper bound of noise eigenvalues, $\lambda_{\max}^{MP}$. Thus, the number of eigenvalues greater than $\lambda_{\max}^{MP}$ corresponds to the total number of incident sources D .

3.1.2. Iterative Algorithm for Source Number Estimation

Given that the true noise power σ_n^2 is unknown, this paper designs an iterative framework to realize unbiased noise power estimation and accurate source number identification. The detailed steps are outlined as follows:

- (a) **Preprocessing:** Perform eigenvalue decomposition on the sample covariance matrix $\hat{\mathbf{R}}$, yielding a descending-sorted eigenvalue sequence $\hat{\lambda}_1 \geq \hat{\lambda}_2 \geq \dots \geq \hat{\lambda}_M$ and the corresponding normalized eigenvector matrix $\hat{\mathbf{U}} = [\hat{\mathbf{u}}_1, \hat{\mathbf{u}}_2, \dots, \hat{\mathbf{u}}_M]$;
- (b) **Initial source number calculation:** Based on the lower bound formula (11) of the MP distribution, the initial noise power estimate is derived by back-calculating from the minimum eigenvalue $\hat{\lambda}_M$:

$$\hat{\sigma}_{n,0}^2 = \hat{\lambda}_M / (1 - \sqrt{c})^2. \quad (12)$$

Using the initial noise power, the initial threshold for noise eigenvalues is computed as:

$$\eta_0 = \hat{\sigma}_{n,0}^2 (1 + \sqrt{c})^2. \quad (13)$$

The initial source number $\hat{D}_0$ is obtained by counting the number of eigenvalues exceeding the initial threshold. It is worth noting that Equation (12) relies solely on the single minimum eigenvalue for back-calculation; under limited snapshots, this estimate is not unbiased. However, as an initial value, it enables rapid convergence, and its bias will be corrected in subsequent steps;

- (c) **Iterative optimization:** Based on the current source number $\hat{D}_t$, the noise subspace is separated, and the mean of all eigenvalues in the noise subspace (denoted as $\bar{\lambda}_{\text{noise}}$) is computed. Leveraging the unbiased estimation property of the mean eigenvalue of the noise subspace in Random Matrix Theory (RMT), the noise power estimate is updated as:

$$\hat{\sigma}_{n,t+1}^2 = \frac{\bar{\lambda}_{\text{noise}}}{1 + c}. \quad (14)$$

The theoretical basis of Equation (14) stems from the first-moment property of the MP distribution: for a noise-only sample covariance matrix, the asymptotic expectation of the mean eigenvalue of the noise subspace is $\sigma_n^2 (1 + c)$. Thus, an asymptotically unbiased noise power estimate is obtained by dividing by the factor $(1 + c)$. Compared to the initial estimate based on a single minimum eigenvalue, this method utilizes the statistical information of all noise eigenvalues, leading to a significant improvement in robustness. Using the updated noise power, the noise eigenvalue threshold is recalculated:

$$\eta_{t+1} = \hat{\sigma}_{n,t+1}^2 (1 + \sqrt{c})^2. \quad (15)$$

The current source number $\hat{D}_{t+1}$ is determined by counting the number of eigenvalues exceeding the updated threshold;

- (d) **Convergence check and boundary constraints:** If $\hat{D}_{t+1} = \hat{D}_t$, the iteration converges. Otherwise, set $\hat{D}_t = \hat{D}_{t+1}$ and repeat the iterative process in Step (c). Upon convergence, the final estimated source number $\hat{D}$ and the unbiased noise power estimate $\hat{\sigma}_n^2$ are obtained. This noise power estimate is an unbiased estimator for white noise scenarios and is unaffected by signal power or steering vector mismatches.

3.2. Theory of Correlation Between Steering Vectors and Eigenvectors

This section rigorously derives the correlation between the steering vector of the desired signal and the eigenvectors of the array covariance matrix, thereby providing theoretical underpinnings for the coarse estimation method of the desired signal's SNR based on correlation coefficient matching in Section 4.3.

3.2.1. Covariance Matrix Decomposition in Dual-Source Scenarios

To streamline the derivation process, this paper conducts analysis based on a typical scenario with one desired signal and one interference signal. Herein, the array covariance matrix can be expressed as:

$$\mathbf{R} = \sigma_s^2 \mathbf{a}(\theta_0) \mathbf{a}^H(\theta_0) + \sigma_{f,1}^2 \mathbf{a}(\theta_1) \mathbf{a}^H(\theta_1) + \sigma_n^2 \mathbf{I}_M. \quad (16)$$

In accordance with subspace theory, for a two-source scenario, the dimension of the signal subspace is 2, and any eigenvector within the signal subspace can be represented as a linear combination of the steering vectors corresponding to the desired signal and the interference signal.

$$\mathbf{u}_i = \alpha_i \mathbf{a}(\theta_0) + \beta_i \mathbf{a}(\theta_1), \quad i = 1, 2, \quad (17)$$

Herein, α_i and β_i denote the linear combination coefficients, which satisfy the normalization constraint $\|\mathbf{u}_i\|^2 = 1$. In light of the definition of eigenvalues and eigenvectors, i.e., $\mathbf{R}\mathbf{u}_i = \lambda_i \mathbf{u}_i$, substituting Equations (16) and (17) into the above yields:

$$\left[\sigma_s^2 \mathbf{a}(\theta_0) \mathbf{a}^H(\theta_0) + \sigma_{j,1}^2 \mathbf{a}(\theta_1) \mathbf{a}^H(\theta_1) \right] \mathbf{u}_i = (\lambda_i - \sigma_n^2) \mathbf{u}_i. \quad (18)$$

The normalized cross-correlation coefficient of the steering vectors is defined as:

$$\gamma = \frac{\mathbf{a}^H(\theta_0) \mathbf{a}(\theta_1)}{M}, \quad (19)$$

where $|\gamma| \leq 1$: the closer $|\gamma|$ is to 0, the better the orthogonality between the two steering vectors; the closer it is to 1, the stronger their coherence. Leveraging the inner product property of uniform linear array (ULA) steering vectors, i.e., $\mathbf{a}^H(\theta_0) \mathbf{a}(\theta_0) = \mathbf{a}^H(\theta_1) \mathbf{a}(\theta_1) = M$, substituting Equation (17) into Equation (18), followed by expansion and rearrangement, yields:

$$\mathbf{a}(\theta_0) \left[(M\sigma_s^2 - \lambda_i + \sigma_n^2) \alpha_i + M\sigma_s^2 \gamma \beta_i \right] + \mathbf{a}(\theta_1) \left[M\sigma_{j,1}^2 \gamma^* \alpha_i + (M\sigma_{j,1}^2 - \lambda_i + \sigma_n^2) \beta_i \right] = 0. \quad (20)$$

Given the distinct incident angles of the desired signal and the interference signal, their steering vectors $\mathbf{a}(\theta_0)$ and $\mathbf{a}(\theta_1)$ are linearly independent. The necessary and sufficient condition for Equation (20) to hold is that the coefficients corresponding to the two steering vectors are both zero, thereby yielding the following system of algebraic equations:

$$\begin{cases} (M\sigma_s^2 - \lambda_i + \sigma_n^2) \alpha_i + M\sigma_s^2 \gamma \beta_i = 0, \\ M\sigma_{j,1}^2 \gamma^* \alpha_i + (M\sigma_{j,1}^2 - \lambda_i + \sigma_n^2) \beta_i = 0. \end{cases} \quad (21)$$

System (21) can be regarded as a homogeneous linear system in terms of the linear combination coefficients α_i and β_i . The necessary and sufficient condition for this system to admit non-trivial solutions is that the determinant of the coefficient matrix is zero, i.e., as follows:

$$\det \begin{pmatrix} M\sigma_s^2 - \lambda + \sigma_n^2 & M\sigma_s^2 \gamma \\ M\sigma_{j,1}^2 \gamma^* & M\sigma_{j,1}^2 - \lambda + \sigma_n^2 \end{pmatrix} = 0. \quad (22)$$

By solving this determinant equation, a quadratic equation in terms of the eigenvalue λ is obtained:

$$(\lambda - \sigma_n^2)^2 - M(\sigma_s^2 + \sigma_{j,1}^2)(\lambda - \sigma_n^2) + M^2 \sigma_s^2 \sigma_{j,1}^2 (1 - |\gamma|^2) = 0. \quad (23)$$

Solving this characteristic equation yields two eigenvalues within the signal subspace:

$$\begin{cases} \lambda_1 = \frac{M \left(\sigma_s^2 + \sigma_{j,1}^2 + \sqrt{(\sigma_s^2 - \sigma_{j,1}^2)^2 + 4\sigma_s^2 \sigma_{j,1}^2 |\gamma|^2} \right)}{2} + \sigma_n^2, \\ \lambda_2 = \frac{M \left(\sigma_s^2 + \sigma_{j,1}^2 - \sqrt{(\sigma_s^2 - \sigma_{j,1}^2)^2 + 4\sigma_s^2 \sigma_{j,1}^2 |\gamma|^2} \right)}{2} + \sigma_n^2. \end{cases} \quad (24)$$

By eliminating β from System (21), the core relationship among the eigenvector coefficients is derived as follows:

$$\beta = \frac{(\lambda - \sigma_n^2 - M\sigma_s^2)}{M\sigma_s^2 \gamma} \alpha. \quad (25)$$

The prerequisite for Equation (25) to hold is that $\gamma \neq 0$, i.e., the steering vectors of the desired signal and the interference are not strictly orthogonal (the strict orthogonality condition is not meaningful in practical engineering scenarios). By substituting Equation

(25) into Equation (17), the general expressions for the two eigenvectors within the signal subspace are derived as follows:

$$\begin{cases} \mathbf{u}_1 = \alpha_1 \left(\mathbf{a}(\theta_0) + \frac{(\lambda_1 - \sigma_n^2 - M\sigma_s^2)}{M\sigma_s^2\gamma} \mathbf{a}(\theta_1) \right) \\ \mathbf{u}_2 = \alpha_2 \left(\mathbf{a}(\theta_0) + \frac{(\lambda_2 - \sigma_n^2 - M\sigma_s^2)}{M\sigma_s^2\gamma} \mathbf{a}(\theta_1) \right) \end{cases} \quad (26)$$

Equations (24) and (26) serve as the core foundation for the derivations in this section: the structure of eigenvectors is fully determined by their corresponding eigenvalues, while the magnitudes of the eigenvalues are dominated by the power of incident signals. On this basis, the correlation between the steering vector of the desired signal and the eigenvectors within the signal subspace can be derived.

3.2.2. Analysis of the Correlation Coefficients Between the Steering Vector of the Desired Signal and the Eigenvectors

Based on the derivation presented in Section 3.2.1, the two eigenvectors within the signal subspace can be uniformly formulated as:

$$\mathbf{u}_i = \alpha_i \left(\mathbf{a}(\theta_0) + \kappa_i \mathbf{a}(\theta_1) \right), \quad i = 1, 2, \quad (27)$$

where the coefficient $\kappa_i = (\lambda_i - \sigma_n^2 - M\sigma_s^2) / M\sigma_s^2\gamma$ is determined by the corresponding eigenvalue λ_i . The normalized correlation coefficient between the steering vector of the desired signal $\mathbf{a}(\theta_0)$ and the eigenvector $\mathbf{u}_i$ is defined as:

$$\rho_i = \frac{|\mathbf{a}^H(\theta_0)\mathbf{u}_i|}{\|\mathbf{a}(\theta_0)\| \cdot \|\mathbf{u}_i\|} = \frac{1}{\sqrt{M}} |\mathbf{a}^H(\theta_0)\mathbf{u}_i|. \quad (28)$$

Substituting the expression for $\mathbf{u}_i$ yields $\mathbf{a}^H(\theta_0)\mathbf{u}_i = \alpha_i M (1 + \kappa_i \gamma)$. From the normalization condition $\|\mathbf{u}_i\| = 1$, we obtain:

$$|\alpha_i| = \frac{1}{\sqrt{M(1 + 2\kappa_i\gamma + |\kappa_i|^2)}}. \quad (29)$$

By rotating the array reference point, γ can be transformed into a positive real number (without affecting the magnitude of the correlation coefficient). Thus, we assume $\gamma > 0$ and κ_i to be real numbers in the following derivation, which gives:

$$\rho_i = \frac{|1 + \kappa_i\gamma|}{\sqrt{1 + 2\kappa_i\gamma + \kappa_i^2}}. \quad (30)$$

By introducing the variable $t_i = \kappa_i\gamma$, we obtain:

$$\rho_i^2 = \frac{1}{1 + \frac{t_i^2}{(1+t_i)^2} (1/\gamma^2 - 1)}. \quad (31)$$

From Equation (31), it is evident that ρ_i^2 exhibits a strictly inverse proportional relationship with $g(t_i) = t_i^2 / (1+t_i)^2$; thus, the magnitude of the correlation coefficient is fully determined by $g(t_i)$. Substituting Equation (24) into the expression for t_i yields the simplified result:

$$\begin{cases} t_1 = \frac{(\sigma_{j,1}^2 - \sigma_s^2) + \sqrt{(\sigma_s^2 - \sigma_{j,1}^2)^2 + 4\sigma_s^2\sigma_{j,1}^2\gamma^2}}{2\sigma_s^2}, \\ t_2 = \frac{(\sigma_{j,1}^2 - \sigma_s^2) - \sqrt{(\sigma_s^2 - \sigma_{j,1}^2)^2 + 4\sigma_s^2\sigma_{j,1}^2\gamma^2}}{2\sigma_s^2}. \end{cases} \quad (32)$$

In the following, we conduct an analysis by categorizing three typical scenarios, comparing the magnitudes of $g(t_1)$ and $g(t_2)$, and further determining the relative magnitude relationship between ρ_1^2 and ρ_2^2 .

Case A: The power of the desired signal is significantly larger than that of the interference signal.

Let $\epsilon = \sigma_{j,1}^2 / \sigma_s^2 \ll 1$; substituting this into Equation (24) yields:

$$\begin{cases} \lambda_1 \approx \sigma_n^2 + M\sigma_s^2(1 + \epsilon\gamma^2), \\ \lambda_2 \approx \sigma_n^2 + M\sigma_{j,1}^2(1 - \gamma^2). \end{cases} \quad (33)$$

Since ϵ is a small quantity, Equation (33) implies that $\lambda_1 \gg \lambda_2$, where λ_1 is primarily dominated by the power of the desired signal and λ_2 is mainly governed by the power of the interference signal. Substituting Equation (33) into Equation (32) gives:

$$\begin{cases} t_1 \approx \epsilon\gamma^2, \\ t_2 \approx \epsilon(1 - \gamma^2) - 1. \end{cases} \quad (34)$$

Given that t_1 is a very small positive value, $g(t_1) \approx t_1^2 \approx \epsilon^2\gamma^4$ takes an extremely small value, while $g(t_2) \approx 1 / [\epsilon(1 - \gamma^2)]^2$ is much larger. Thus, $g(t_2) \gg g(t_1)$ and $\rho_1^2 \gg \rho_2^2$. This indicates that the steering vector of the desired signal has a significantly larger correlation coefficient with the eigenvector $\mathbf{u}_1$ corresponding to the larger eigenvalue λ_1 dominated by the desired signal.

Case B: The power of the desired signal is comparable to that of the interference signal

In this scenario, the power of the desired signal is comparable to that of the interference signal. Considering the extreme case where $\sigma_s^2 = \sigma_{j,1}^2 = P$, substituting this into Equation (24) yields:

$$\begin{cases} \lambda_1 = MP(1 + \gamma) + \sigma_n^2, \\ \lambda_2 = MP(1 - \gamma) + \sigma_n^2. \end{cases} \quad (35)$$

In this case, $t_1 = \gamma$ and $t_2 = -\gamma$. Substituting these into Equation (31) gives:

$$\begin{cases} \rho_1^2 = \frac{1 + \gamma}{2}, \\ \rho_2^2 = \frac{1 - \gamma}{2}. \end{cases} \quad (36)$$

Since $\gamma > 0$, it is evident that $\rho_1^2 > \rho_2^2$. Thus, the steering vector of the desired signal has a larger correlation coefficient with the eigenvector $\mathbf{u}_1$ corresponding to the larger eigenvalue λ_1 . Even though the power of the desired signal is equal to that of the interference signal, λ_1 can still be regarded as being dominated by the power of the desired signal.

Case C: The power of the interference signal is significantly larger than that of the desired signal

Let $\eta = \sigma_s^2 / \sigma_{j,1}^2 \ll 1$, where the desired signal is weak, and the interference is strong. Substituting this into Equation (24) yields:

$$\begin{cases} \lambda_1 \approx \sigma_n^2 + M\sigma_{j,1}^2(1 + \eta\gamma^2), \\ \lambda_2 \approx \sigma_n^2 + M\sigma_s^2(1 - \gamma^2). \end{cases} \quad (37)$$

Since η is a small quantity, $\lambda_1 \gg \lambda_2$, with λ_1 primarily dominated by the interference power and λ_2 mainly governed by the desired signal power. Substituting Equation (37) into Equation (32) gives:

$$\begin{cases} t_1 \approx 1/\eta, \\ t_2 \approx -\gamma^2. \end{cases} \quad (38)$$

At this point, $g(t_1) \approx 1 - 2\eta \approx 1$ and $g(t_2) = [\gamma^2 / (1 - \gamma^2)]^2$. When $\gamma^2 < 1/2$, $g(t_2) < 1$ while $g(t_1) \approx 1 > g(t_2)$, thus $\rho_1^2 < \rho_2^2$. In this scenario, the steering vector of the desired signal has a higher correlation coefficient with the eigenvector $\mathbf{u}_2$ corresponding to the smaller eigenvalue λ_2 . As confirmed by power analysis, λ_2 is precisely the eigenvalue dominated by the desired signal, indicating correct matching.

When $\gamma^2 > 1/2$, $g(t_2) > 1$, so $g(t_2) > g(t_1) \approx 1$, leading to $\rho_1^2 > \rho_2^2$. This implies that the steering vector of the desired signal exhibits a higher correlation with the eigenvector $\mathbf{u}_1$ associated with the larger eigenvalue λ_1 . However, under this power configuration, λ_1 is interference-dominated. If the maximum correlation coefficient criterion is still applied for matching, the interference-dominant eigenvector would be incorrectly identified as the desired signal component, resulting in severe errors in subsequent power estimation. Therefore, direct application of the maximum correlation coefficient criterion requires satisfying the spatial separation condition between the signal and interference: $\gamma^2 < 1/2$.

Based on the derivations across the three scenarios, this paper presents the following core conclusion: For a ULA receiving scenario with narrowband far-field signals, when the spatially normalized cross-correlation coefficient between the desired signal and interference satisfies $\gamma^2 < 1/2$, the normalized correlation coefficient between the desired signal steering vector $\mathbf{a}(\theta_0)$ and the desired-signal-dominated eigenvector within the signal subspace of the array covariance matrix is always the maximum among all eigenvectors in the signal subspace. In practical non-cooperative interference environments, interference sources and the desired transmitter are typically located at distinct geographical positions, leading to inherent physical differences in their spatial arrival angles. Perfect spatial alignment between the interference and the desired signal is thus difficult to achieve. Therefore, calculating the normalized correlation coefficients between all eigenvectors in the signal subspace and the a priori desired steering vector, and selecting the eigenvector with the highest correlation coefficient as the desired-signal-dominated eigenvector, is both reasonable and robust in practical applications. This conclusion provides the theoretical foundation for the desired-signal eigenvalue matching step in Section 4.3 and also delineates the applicable boundaries of the algorithm. The above analysis is conducted under the single-interference model. A rigorous generalization of the maximum-correlation criterion to scenarios with an arbitrary number of interferers, based on matrix perturbation theory, is provided in Appendix B.

It is worth noting that Case A among the three scenarios exhibits unique estimation properties: The desired-signal-dominated eigenvalue is almost entirely determined by its own power, while the interference contribution is merely a second-order small quantity. This implies that when the desired signal power dominates, high-precision results can be obtained by directly estimating the desired signal power from the eigenvalues, without the need for spatial filtering to decouple power components. This observation provides

the theoretical basis for introducing a strategy-switching mechanism based on coarse SIR estimation in the subsequent algorithm.

4. Design of an Adaptive and Robust SINR Estimation Algorithm

To mitigate the performance degradation of the Capon power spectrum estimation algorithm under scenarios with limited snapshots and desired signal steering vector mismatches, this section proposes a progressive SINR estimation algorithm based on the fundamental theory in Section 2 and core mechanism analysis in Section 3. The algorithm employs a two-stage framework: feature subspace-based coarse estimation followed by robust Capon-based fine estimation.

4.1. Overall Architecture of the Algorithm

This algorithm employs a two-stage progressive framework, feature subspace-based coarse estimation followed by robust Capon-based fine estimation, consisting of the following four sequential modules:

- (a) Source number estimation and noise power extraction via the MP law under limited snapshot conditions;
- (b) Coarse estimation of the desired signal power is obtained via correlation coefficient matching, followed by strategy discrimination based on the coarsely estimated SIR;
- (c) In scenarios where the desired signal power is non-dominant, adaptive diagonal loading and refined Capon estimation are implemented;
- (d) Interference power inference through the trace identity, enabling closed-loop SINR computation.

Notably, the coarse estimation in Step 2 serves a dual function: in scenarios where the desired signal power is non-dominant, it drives the diagonal loading process; in dominant cases, it is directly output as the final desired signal power estimate (see Section 4.3 for the decision criterion).

4.2. Estimation of Source Number and Noise Power

Based on the iterative MP-law source number estimation method proposed in Section 3.1, iterative processing is applied to the sample covariance matrix $\hat{\mathbf{R}}$. After convergence of the iteration, the estimated source number $\hat{D}$ and an unbiased estimate of noise power $\hat{\sigma}_n^2$ are obtained. Based on $\hat{D}$, the signal subspace $\hat{\mathbf{U}}_s = [\hat{\mathbf{u}}_1, \dots, \hat{\mathbf{u}}_{\hat{D}}]$ and the noise subspace $\hat{\mathbf{U}}_n = [\hat{\mathbf{u}}_{\hat{D}+1}, \dots, \hat{\mathbf{u}}_M]$ are separated. This noise power estimate is an asymptotically unbiased estimator of noise power under white noise conditions and is unaffected by mismatches in signal power or steering vectors.

4.3. Coarse Estimation of Desired Signal Power via Correlation Coefficient Matching

Leveraging the findings in Section 3.2.2, the eigenvalue dominated by the desired signal is localized through correlation coefficient matching between the steering vector and eigenvectors. This enables coarse estimation of the SNR, which serves as the core input parameter for subsequent adaptive diagonal loading calculation. The detailed implementation steps are as follows:

- (a) Compute the normalized correlation coefficient between each eigenvector $\hat{\mathbf{u}}_i$ ($i = 1, 2, \dots, \hat{D}$) and the nominal desired steering vector $\hat{\mathbf{a}}(\theta_0)$ using Equation (28);
- (b) Identify the eigenvalue $\hat{\lambda}_s$ corresponding to the eigenvector associated with the maximum correlation coefficient $\rho_{\max} = \max\{\rho_1, \rho_2, \dots, \rho_{\hat{D}}\}$; this eigenvalue is domi-

nated by the desired signal. Utilizing the eigenvalue structure relationship $\hat{\lambda}_s \approx M\sigma_s^2 + \sigma_n^2$, the coarse estimate of the desired signal power is derived as:

$$\hat{\sigma}_{s,\text{rough}}^2 = \frac{\hat{\lambda}_s - \sigma_n^2}{M}. \quad (39)$$

From the analysis in Section 3.2.2, it is evident that, when the desired signal power is significantly higher than the interference power, the dominant eigenvalue corresponding to the desired signal within the signal subspace becomes completely decoupled from the interference eigenvalues, and the coarse estimate given by Equation (39) already achieves high accuracy. However, when the desired signal power is comparable to the interference power, or when the desired signal is weak, and the steering vectors of the interference signals are highly correlated with that of the desired signal, eigenvalue coupling occurs, resulting in insufficient accuracy of the coarse estimate, necessitating a refined estimation through subsequent Capon spatial filtering. Based on this, scene classification is performed using the obtained coarse estimates. First, the total interference power is coarsely estimated using the trace identity:

$$\hat{\sigma}_{j,\text{rough}}^2 = \frac{1}{M} \text{tr}(\hat{\mathbf{R}}) - \hat{\sigma}_{s,\text{rough}}^2 - \sigma_n^2. \quad (40)$$

The coarse estimate of the SIR is obtained from Equations (39) and (40):

$$SIR_{\text{rough}} = \frac{\hat{\sigma}_{s,\text{rough}}^2}{\hat{\sigma}_{j,\text{rough}}^2}. \quad (41)$$

A threshold κ is predefined. If $SIR_{\text{rough}} \geq \kappa$, the current scenario is classified as the desired signal power-dominant regime. The coarse estimate is directly adopted as the final desired signal power estimate, i.e., $\hat{\sigma}_s^2 = \hat{\sigma}_{s,\text{rough}}^2$. The fine estimation steps in Sections 4.4 and 4.5 are skipped, with direct progression to the SINR calculation in Section 4.5. If $SIR_{\text{rough}} < \kappa$, the current scenario is classified as the non-dominant desired signal power regime, where eigenvalue coupling and signal self-cancellation risk coexist. In this case, $\hat{\sigma}_{s,\text{rough}}^2$ serves as the core parameter to drive both the adaptive diagonal loading in Section 4.4 and the robust Capon fine estimation in Section 4.5.

4.4. Closed-Form Solution for Optimal Adaptive Diagonal Loading

In Section 2.4, the steering vector mismatch error $\mathbf{e}$ is modeled as a complex Gaussian random vector $\mathbf{e} \sim \mathcal{CN}(0, \sigma_e^2 \mathbf{I}_M)$. To develop a loading strategy robust to all admissible errors, this section reformulates the random error model into a deterministic norm-constrained framework. Specifically, the mismatch error vector $\mathbf{e}$ is constrained to satisfy $\|\mathbf{e}\| \leq \varepsilon_{\text{max,abs}}$, where $\varepsilon_{\text{max,abs}}$ denotes the absolute error magnitude upper bound; this bound can be derived from the mismatch variance σ_e^2 and a pre-specified confidence probability. The diagonal-loaded covariance matrix is expressed as $\mathbf{R}_L = \hat{\mathbf{R}} + \xi \mathbf{I}_M$, where $\xi \geq 0$ is the diagonal loading factor to be determined. The optimal Capon weight vector under diagonal loading is given by:

$$\mathbf{w}_L = \frac{\mathbf{R}_L^{-1} \hat{\mathbf{a}}(\theta_0)}{\hat{\mathbf{a}}^H(\theta_0) \mathbf{R}_L^{-1} \hat{\mathbf{a}}(\theta_0)}. \quad (42)$$

In the presence of steering vector mismatch, the constraint fails to enforce on the true steering vector $\mathbf{a}(\theta_0)$. The Capon optimization framework will misclassify the true desired signal as interference and apply suppression, leading to a response gain for the true desired signal below unity. The response gain for the true desired signal is formulated as:

$$G = \mathbf{w}_L^H \mathbf{a}(\theta_0) = \mathbf{w}_L^H (\hat{\mathbf{a}}(\theta_0) - \mathbf{e}) = 1 - \mathbf{w}_L^H \mathbf{e}. \quad (43)$$

By virtue of the Cauchy–Schwarz inequality, for any error vector satisfying the constraint $\|\mathbf{e}\| \leq \varepsilon_{\max, \text{abs}}$, the following holds:

$$|\mathbf{w}_L^H \mathbf{e}| \leq \|\mathbf{w}_L\| \cdot \|\mathbf{e}\| \leq \varepsilon_{\max, \text{abs}} \cdot \|\mathbf{w}_L\|. \quad (44)$$

The worst-case scenario arises when the error vector $\mathbf{e}$ is fully aligned with the weight vector $\mathbf{w}_L$, whereupon the gain attains its global minimum:

$$G_{\min} = 1 - \varepsilon_{\max, \text{abs}} \cdot \|\mathbf{w}_L\|. \quad (45)$$

The primary optimization objective of this section is to select the minimum diagonal loading factor ξ that minimizes the estimation bias introduced by loading, while guaranteeing no signal self-nulling in the worst-case scenario $G_{\min} \geq 0$. This objective is equivalent to solving the following constrained optimization problem:

$$\begin{aligned} \min_{\xi \geq 0} \quad & \xi \\ \text{s.t.} \quad & 1 - \varepsilon_{\max, \text{abs}} \cdot \|\mathbf{w}_L(\xi)\| \geq 0. \end{aligned} \quad (46)$$

It can be proven that the norm of the weight vector $\|\mathbf{w}_L\|$ is a strictly monotonically decreasing function of ξ (see Appendix A for the complete proof). The larger the diagonal loading, the closer the Capon weight vector approaches the conventional beamforming weights, resulting in a smaller norm and weaker signal self-cancellation effect, but also reduced interference suppression capability. Based on this monotonicity, the optimal solution must occur where the constraint holds with equality, i.e.,

$$\|\mathbf{w}_L(\xi_{\text{opt}})\| = \frac{1}{\varepsilon_{\max, \text{abs}}}. \quad (47)$$

To derive a closed-form solution for ξ_{opt} from condition (47), this section adopts the robust Capon beamforming (RCB) theoretical framework proposed in [21]. The core rationale of the RCB method is to transform the diagonal loading factor determination problem into a scalar equation root-finding problem via eigen-decomposition of the covariance matrix, under the norm-ball constraint on steering vector errors.

The diagonally loaded covariance matrix is expressed as $\mathbf{R}_L = \hat{\mathbf{R}} + \xi \mathbf{I}_M = \hat{\mathbf{U}}(\hat{\mathbf{\Lambda}} + \xi \mathbf{I}_M)\hat{\mathbf{U}}^H$. By virtue of the properties of eigen-decomposition, $\mathbf{R}_L^{-1}$ can be derived as:

$$\mathbf{R}_L^{-1} = \hat{\mathbf{U}}(\hat{\mathbf{\Lambda}} + \xi \mathbf{I}_M)^{-1} \hat{\mathbf{U}}^H = \sum_{m=1}^M \frac{\hat{\mathbf{u}}_m \hat{\mathbf{u}}_m^H}{\hat{\lambda}_m + \xi}. \quad (48)$$

Project the a priori steering vector $\hat{\mathbf{a}}(\theta_0)$ onto the eigenvector basis of $\hat{\mathbf{R}}$, denote the projection coefficients as $z_m = \hat{\mathbf{u}}_m^H \hat{\mathbf{a}}(\theta_0)$, and substitute Equation (48) into the expression for the weight vector in Equation (42). We then obtain:

$$\mathbf{w}_L = \sum_{m=1}^M \frac{z_m \hat{\mathbf{u}}_m}{\hat{\lambda}_m + \xi} \bigg/ \sum_{m=1}^M \frac{|z_m|^2}{\hat{\lambda}_m + \xi}. \quad (49)$$

From Equation (49), the square of the weight vector norm can be exactly expressed as:

$$\|\mathbf{w}_L\|^2 = \sum_{m=1}^M \frac{|z_m|^2}{(\hat{\lambda}_m + \xi)^2} \bigg/ \left(\sum_{m=1}^M \frac{|z_m|^2}{\hat{\lambda}_m + \xi} \right)^2. \quad (50)$$

Substituting Equation (50) into the squared form of the optimality condition (47) $\|\mathbf{w}_L\|^2 = 1/\varepsilon_{\max, \text{abs}}^2$, a scalar equation with respect to ξ is obtained:

$$\sum_{m=1}^M \frac{|z_m|^2}{(\hat{\lambda}_m + \xi)^2} \bigg/ \left(\sum_{m=1}^M \frac{|z_m|^2}{\hat{\lambda}_m + \xi} \right)^2 = 1/\varepsilon_{\max, \text{abs}}^2. \quad (51)$$

Equation (51) serves as the core equation within the RCB framework; given $\varepsilon_{\max, \text{abs}}$ and the eigen-system $(\hat{\lambda}_m, z_m)$, the optimal diagonal loading factor ξ_{opt} can be obtained via numerical solution.

In typical non-cooperative interference scenarios, the power of the desired signal and interference is significantly greater than the noise power, and the incident angle difference between the desired signal and interference exceeds the array's half-power beamwidth (their steering vectors are approximately orthogonal). As elaborated in Section 3.2, under these conditions, the desired signal component in the signal subspace of the sample covariance matrix is concentrated exclusively on the unique eigenvalue $\hat{\lambda}_s$, and the corresponding eigenvector $\hat{\mathbf{u}}_s$ exhibits high correlation with the prior steering vector $\hat{\mathbf{a}}(\theta_0)$, i.e., $|z_s|^2 \gg |z_m|^2 (m \neq s)$.

Based on the above analysis, the summation in the denominator of Equation (51) is dominated by the term corresponding to the desired signal eigenvalue, leading to the approximation

$$\sum_{m=1}^M \frac{|z_m|^2}{\hat{\lambda}_m + \xi} \approx \frac{|z_s|^2}{\hat{\lambda}_s + \xi} \approx \frac{M}{\hat{\lambda}_s + \xi}. \quad \text{The numerator term can be approximated as}$$

$$\sum_{m=1}^M \frac{|z_m|^2}{(\hat{\lambda}_m + \xi)^2} \approx \frac{M}{(\hat{\lambda}_s + \xi)^2} + \frac{\varepsilon_{\max, \text{abs}}^2}{\xi^2}. \quad \text{Thus, Equation (51) can be approximated as:}$$

$$\frac{1}{M} + \frac{\varepsilon_{\max, \text{abs}}^2}{\xi^2} \cdot \frac{(\hat{\lambda}_s + \xi)^2}{M^2} = \frac{1}{\varepsilon_{\max, \text{abs}}^2}. \quad (52)$$

According to Equation (52), the exact closed-form solution for the optimal diagonal loading factor is expressed as:

$$\xi_{\text{opt}} = \frac{\hat{\lambda}_s}{\frac{M}{\varepsilon_{\max, \text{abs}}} \sqrt{\frac{1}{\varepsilon_{\max, \text{abs}}^2} - \frac{1}{M}} - 1} \quad (53)$$

4.5. Robust Capon Power Refined Estimation and SINR Closed-Loop Calculation

In Section 4.3, we have derived a coarse estimate of the desired signal power via correlation coefficient matching and completed strategy discrimination based on the rough SIR. This section focuses on the scenario where the discrimination result satisfies $\text{SIR}_{\text{rough}} < \kappa$, where eigenvalue coupling and signal self-cancellation risk coexist. To address this, refined estimation is performed using diagonal loading and Capon spatial filtering. Substituting the optimal diagonal loading factor ξ_{opt} into the original sample covariance matrix yields the modified sample covariance matrix:

$$\mathbf{R}_{\text{robust}} = \hat{\mathbf{R}} + \xi_{\text{opt}} \mathbf{I}_M. \quad (54)$$

A key caveat must be emphasized: diagonal loading is exclusively employed to mitigate the signal self-nulling effect in Capon spectrum estimation. In contrast, the total power calculation strictly retains the original sample covariance matrix to avoid loading-induced total power bias.

Based on the modified covariance matrix, the Capon spatial spectrum estimation method is utilized to compute the desired signal power. For the a priori steering vector $\hat{\mathbf{a}}(\theta_0)$, the robust refined estimate of the desired signal power is formulated as:

$$\hat{\sigma}_s^2 = \frac{1}{\hat{\mathbf{a}}^H(\theta_0) \mathbf{R}_{\text{robust}}^{-1} \hat{\mathbf{a}}(\theta_0)}. \quad (55)$$

By leveraging the fundamental property of the array covariance matrix, the total received power of the array is equal to the sum of all its eigenvalues; the estimated average total interference power per antenna is derived as:

$$\hat{\sigma}_j^2 = \frac{1}{M} \text{tr}(\hat{\mathbf{R}}) - \hat{\sigma}_s^2 - \hat{\sigma}_n^2. \quad (56)$$

The estimated SINR is ultimately defined as the ratio of the desired signal power to the total interference-plus-noise power:

$$\text{SINR}_{\text{Estimated}} = \frac{\hat{\sigma}_s^2}{\hat{\sigma}_j^2 + \hat{\sigma}_n^2}. \quad (57)$$

5. Simulation Results

This section systematically validates the performance advantages and applicable scope of the proposed algorithm under multiple non-ideal conditions (including non-cooperative strong interference, limited snapshots, and steering vector mismatches) through a series of Monte Carlo simulation experiments. The validation encompasses four dimensions: source number estimation accuracy, effectiveness of internal strategies, performance bounds of spatial resolution, and horizontal comparison with mainstream blind estimation algorithms such as RMT-BSE, M2M4, SSME, and SNV. The simulation parameters are presented in Table 1. Table 1 summarizes the common baseline parameters shared by all simulation experiments. For each specific sub-experiment, its tailored variable parameters will be further described in the corresponding subsection.

Table 1. Common baseline simulation parameter configuration. Specific variable parameters for each sub-experiment are detailed in the corresponding subsections.

Parameters	Value	Parameters	Value
Number of array elements	10	Modulation scheme of interference 1	QPSK
Element spacing	$\lambda/2$	Bandwidth of interference 1	4 MHz
Array form	ULA	Modulation scheme of interference 2	16QAM
Modulation scheme of desired signal	QPSK	Bandwidth of interference 2	4 MHz
Bandwidth of desired signal	4 MHz	DOA of interference 1	-7°
DOA of desired signal	0°	DOA of interference 2	17°
Monte Carlo iterations	10,000	Interference-to-Noise Ratio (INR)	30 dB

5.1. Performance of Source Number Estimation and Noise Power Estimation

5.1.1. Performance Analysis of Source Number Estimation

This section compares the proposed iterative source number estimation method based on the MP rule with classical criteria, Akaike Information Criterion (AIC), Minimum Description Length (MDL), and Gerschgorin Disks Estimation (GDE), through Monte Carlo simulation experiments, to verify its performance advantages in non-cooperative interference scenarios. The experimental design covers two typical simulation conditions: (a) a fixed number of snapshots, with the expected signal SNR varying from -10 dB to 50 dB in 5 dB steps; (b) a fixed SNR of 10 dB, with the number of snapshots ranging from 50 to 500 in 50 -step increments. The performance of all methods is evaluated using the probability of correct detection as a unified metric. Figure 1 shows the probability of correct detection curves for each method under the above two simulation conditions.

As shown in Figure 1, the proposed iterative source number estimation method based on the MP law demonstrates optimal performance across the entire parameter range, significantly outperforming traditional criteria such as AIC, MDL, and GDE. Specifically, in low SNR and small snapshot regions, the detection probability of the MP algorithm clearly surpasses that of other methods: at SNR = -10 dB, the MP algorithm

achieves a detection probability of 66.46%, while AIC reaches only about 61.41%. In contrast, MDL tends to underestimate due to its overly strong penalty term, resulting in a detection probability near 0%. At low snapshot numbers, the MP algorithm maintains a detection probability of 47.11%, compared to 17.85% for AIC; similarly, MDL suffers from amplified penalty effects under small sample conditions, leading to nearly zero detection probability. In medium-to-high SNR and large snapshot regions, both MP and MDL achieve 100% correct detection probability, whereas AIC inherently faces overestimation risks and fails to reach 100%. The GDE criterion performs poorly in this experimental setting, achieving 100% detection probability only within a narrow SNR range of 15–40 dB, and completely fails under low or high SNR conditions and across all snapshot sizes. The proposed iterative source number estimation method based on the MP law directly characterizes the precise statistical boundary of noise eigenvalues under finite snapshots by leveraging the MP distribution, without relying on ideal assumptions of equal noise eigenvalues or large-sample approximations. This makes it naturally robust against eigenvalue fluctuations caused by limited snapshots. Moreover, the MP algorithm makes decisions solely based on whether eigenvalues exceed their theoretical upper bound, independent of relative differences among eigenvalues, enabling stable operation even in scenarios where strong interference coexists with weak signals. In contrast, AIC and MDL rely on information-theoretic principles and assume Gaussian white noise along with large sample asymptotics, leading to significant performance degradation under small samples and low SNR conditions. Meanwhile, GDE depends on the Gershgorin disk theorem and relies on the relative differences in disk radii; strong interference severely distorts the covariance matrix structure, causing complete loss of distinguishability between signal and noise disks.

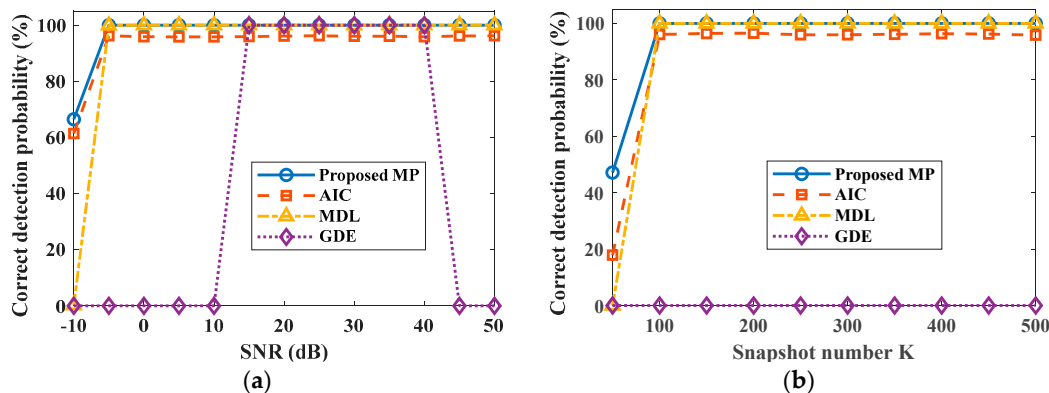


Figure 1. Performance of source number estimation: (a) comparison of correct detection probability of source number at different SNRs; (b) comparison of correct source number detection probability for different snapshot counts.

5.1.2. Accuracy Analysis of Noise Power Estimation

Based on the simulation data generated in Section 5.1.1, this section conducts a quantitative assessment of the noise power estimation performance embedded in the proposed iterative source number estimation method based on the MP law. Two key metrics are adopted for evaluation: the root mean square error (RMSE) and estimation bias (BIAS). The corresponding results are presented in Figure 2.

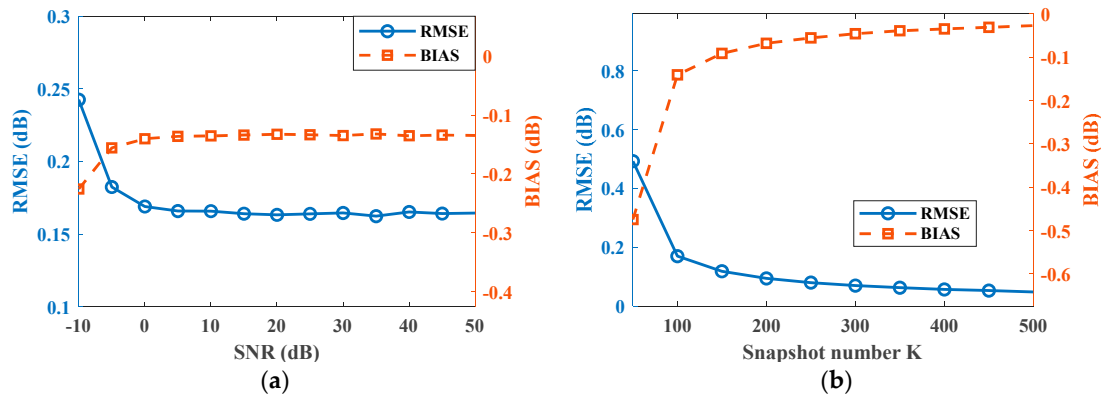


Figure 2. Performance of noise power estimation: (a) performance of noise power estimation under different SNR conditions; (b) noise power estimation error under different snapshot counts.

Simulation results indicate that the estimation accuracy of the proposed method improves significantly and converges rapidly with increasing SNR and snapshot count. **SNR Dimension:** When $\text{SNR} \geq 0$ dB, the RMSE of noise power estimation stabilizes within 0.17 dB, and the BIAS remains around -0.13 dB, exhibiting negligible variation even as SNR increases further. **Snapshot Dimension:** At a snapshot count of 100, the RMSE drops to 0.17 dB, and the BIAS decreases to -0.14 dB; as the snapshot count rises to 500, the RMSE further reduces below 0.05 dB, with the BIAS approaching zero. Notably, even under extreme conditions ($\text{SNR} = -10$ dB and a very small snapshot count), the method still achieves RMSE values of 0.24 dB and 0.49 dB, respectively, demonstrating excellent robustness. Overall, the proposed method achieves high-precision noise power estimation across the entire parameter range, providing reliable prior noise power information for subsequent SINR estimation algorithms.

5.2. Analysis of Parameter Sensitivity

The strategy switching threshold serves as the core control parameter of the proposed algorithm. Its value directly defines the switching boundary between the two estimation modes, balancing the low-complexity advantage of coarse estimation and the robustness advantage of fine estimation and thereby determining the algorithm's estimation accuracy across all scenarios. To identify the optimal threshold configuration and validate the algorithm's sensitivity to this parameter, we fix the snapshot count at $K = 100$ and perform an equidistant step scan of thresholds within the range of 0–15 dB. We then analyze the impact pattern of the threshold on the average RMSE across the full SNR range, providing an optimal parameter basis for subsequent validation of the algorithm's strategy effectiveness.

Figure 3 presents the impact curve of the strategy switching threshold on the algorithm's average RMSE across the full SNR range. The performance exhibits a single-valley characteristic: it first decreases rapidly and then rises slowly. The optimal threshold is determined to be 9 dB, corresponding to a minimum average RMSE of 0.827 dB. In the low-threshold region, the algorithm over-relies on coarse eigenvalue estimation, leading to fundamental bias caused by eigenvalue coupling; when the threshold is increased to 9 dB, an optimal balance is achieved between the low-error advantage of coarse estimation (in high SIR scenarios) and the robustness of Capon fine estimation (in low SIR scenarios); beyond 9 dB, redundant Capon fine estimation in high SIR scenarios introduces additional numerical errors, resulting in a gradual degradation of overall performance.

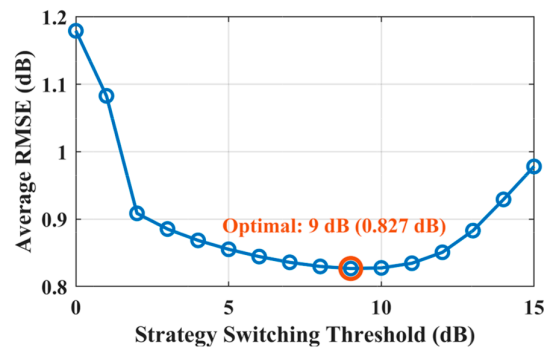


Figure 3. Impact of strategy switching threshold on average RMSE over the entire SNR range.

The optimal threshold $\kappa = 9$ dB is consistent with the physical insight from the theoretical analysis in Section 3.2.2: when the desired signal power exceeds the total interference power by approximately 9 dB, the desired-signal-dominated eigenvalue is sufficiently decoupled from interference eigenvalues (Case A), and the coarse estimate already provides reliable accuracy. More importantly, the RMSE remains stable across a broad range of $\kappa \in [4, 13]$ dB with less than 0.1 dB variation, indicating that the algorithm performance is insensitive to the precise threshold value as long as it lies within this physically reasonable range.

5.3. Validation of the Effectiveness of Internal Algorithm Strategies

To verify the necessity and effectiveness of the progressive architecture, strategy switching mechanism, and adaptive diagonal loading technique proposed in this paper, the complete algorithm is compared with four benchmark algorithms: the proposed algorithm without strategy switching, the EVD-based coarse estimation algorithm, the standard Capon algorithm, and the fixed diagonal loading Capon algorithm.

Simulation parameters are consistent with Section 5.2: an additive steering vector mismatch model is adopted, with the single-channel steering vector error variance set to $\sigma_e^2 = 0.01$. The strategy switching threshold is fixed at the optimal value (9 dB) determined in the previous section, and the fixed loading factor is set to 3 times the noise power. A total of 10,000 Monte Carlo simulations are conducted, with RMSE, Standard Deviation (STD), and BIAS as performance metrics.

Figure 4a shows the SINR estimation RMSE curves for different algorithms as a function of SNR, while Figure 4b presents their STD trends. Table 2 summarizes the average performance statistics across the entire SNR range. Figure 4a indicates that both the standard Capon and fixed diagonal loading Capon algorithms suffer from signal self-cancellation effects, causing errors to grow exponentially with increasing SNR, exceeding 4 dB when $\text{SNR} > 20$ dB. The coarse estimation algorithm exhibits relatively high eigenvalue coupling error at low SNR but converges rapidly due to eigenvalue decoupling at high SNR. The non-switching version of our algorithm experiences performance degradation at high SNR due to numerical errors introduced by redundant Capon computations. In contrast, our algorithm with the optimal 9 dB switching threshold achieves the best overall performance across all SNR levels; the average RMSE is 0.83 dB. Figure 4b reveals that the STD of the standard Capon and fixed-loading algorithms continues to increase with SNR. The coarse estimation algorithm shows a sharp peak in STD around the critical point of eigenvalue coupling between 25 and 30 dB. The non-switching algorithm suffers significant stability deterioration at high SNR. In contrast, our switching algorithm achieves an average standard deviation of merely 0.34 dB over the entire SNR range, demonstrating the best estimation consistency. These results confirm the rationality of the progressive architecture: the strategy-switching mechanism effectively balances low error in coarse

estimation under high SIR conditions with the robustness against coupling and self-cancellation offered by refined Capon estimation under low SIR conditions.

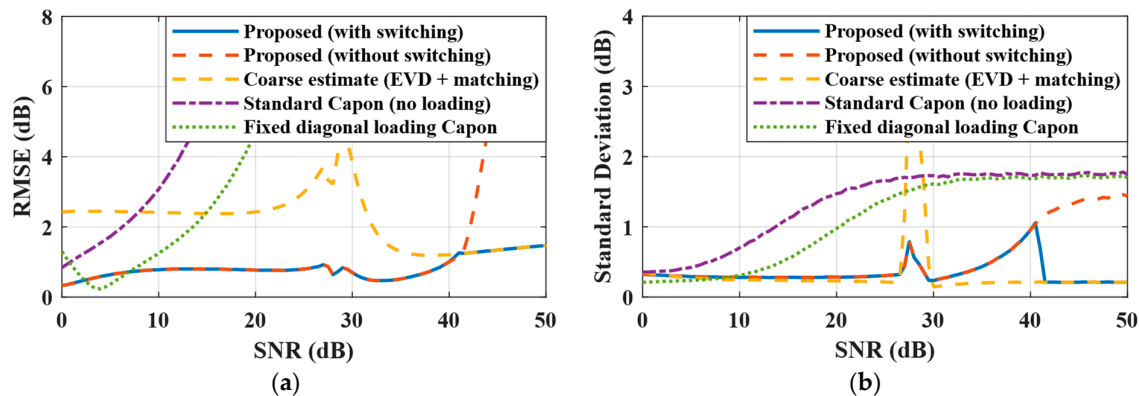


Figure 4. Performance comparison between internal strategies and variants of the proposed algorithm: (a) RMSE of SINR estimation as a function of SNR; (b) STD of SINR estimation as a function of SNR.

Table 2. Internal strategy comparison results.

Algorithm	RMSE (dB)	STD (dB)	BIAS (dB)
Proposed (with switching)	0.83	0.34	0.71
Proposed (without switching)	2.00	0.55	1.84
Coarse estimate (EVD + matching)	2.19	0.32	2.14
Standard Capon (no loading)	19.05	1.34	18.98
Fixed diagonal loading Capon	14.61	1.11	14.54

5.4. Spatial Performance Bound Analysis of the Algorithm

To delineate the spatial applicability boundary of the proposed algorithm, this section performs a two-dimensional grid-scan experiment under a single-interference scenario. This systematic analysis quantifies the joint impact of the angular separation between the desired signal and the interferer, as well as the SNR, on estimation performance. In contrast to multi-interference scenarios, the single-interference setup eliminates coupling-induced interference among multiple interferers. Thereby enabling a cleaner, more interpretable characterization of how spatial separation influences algorithmic performance.

Figure 5 presents the estimation performance comparison of the two algorithms across varying angle differences and SNR levels. The coarse estimation algorithm exhibits extensive high-RMSE regions when the angle difference is less than 8° and at $\text{SNR} \approx 30$ dB (where the desired signal and interference powers are comparable). The root cause lies in severe eigenvalue coupling induced by either highly correlated steering vectors or near-equal power levels, which leads to mismatch errors and power decoupling failure.

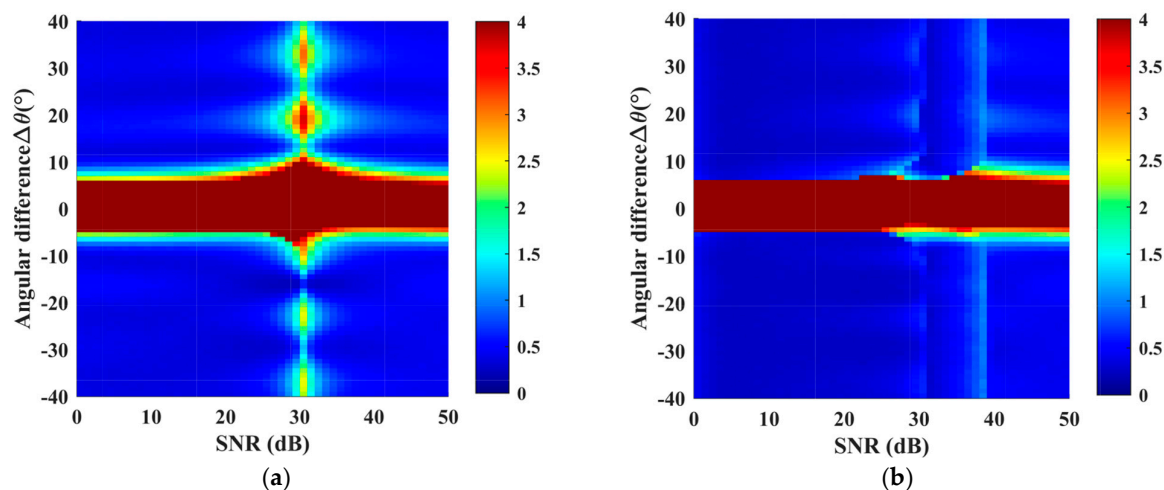


Figure 5. Analysis of spatial applicability boundaries for SINR estimation algorithms: (a) heatmap of RMSE for SINR estimation using the coarse estimation algorithm; (b) heatmap of RMSE for SINR estimation using the proposed algorithm.

In contrast, the proposed algorithm maintains an RMSE below 0.50 dB across the majority of parameter spaces, with only marginal performance degradation observed when the angle difference is less than 6° . This result validates that the robust Capon-based fine estimation module effectively breaks through the spatial resolution limitation of traditional EVD-based methods, thereby significantly expanding the algorithm's applicable boundary.

5.5. Horizontal Comparison with Mainstream Blind Estimation Algorithms

To validate the performance advantages of the proposed algorithm in non-cooperative interference scenarios, this section conducts a horizontal comparison between the proposed algorithm and four mainstream blind SINR estimation algorithms, namely, RMT-BSE, M2M4, SSME, and SNV. The curves of SINR estimation RMSE of different algorithms varying with SNR are depicted in Figure 6a, while the STD curves are presented in Figure 6b. The statistical results of average performance over the entire SNR range are summarized in Table 3. From the RMSE curves, it can be observed that the proposed algorithm maintains optimal performance across the full SNR range, with RMSE stably kept within 1.47 dB. The RMT-BSE algorithm performs well in the low-SNR region; however, when SNR exceeds 25 dB, severe eigenvalue coupling occurs due to the close power levels of the desired signal and interference, leading to a sharp rise in RMSE to over 15 dB. The three statistical-domain algorithms (M2M4, SSME, and SNV) exhibit exponential error growth after SNR exceeds 33.5 dB, 28 dB, and 36 dB, respectively. The fundamental reason is that the interference signal completely replicates the constant modulus property and symbol timing structure of the desired signal, which violates the core assumptions of these three algorithms and makes them unable to distinguish the statistical components of the signal and interference. As shown in the STD curves, the estimation dispersions of the SNV and SSME algorithms approach 0 dB; however, due to their excessively large SINR estimation errors, they have no practical reference value. In contrast, the STD of the proposed algorithm is consistently below 1.02 dB, demonstrating excellent estimation consistency and robustness.

Machine-learning-based SINR estimators are inherently closed-set methods that rely on training data covering the target interference distributions. The non-cooperative interference scenario studied in this paper, however, is an open-set problem: the jammer's characteristics are completely unknown and may differ arbitrarily from any training set,

rendering pre-trained models prone to unpredictable failures. In contrast, the proposed algorithm is model-based, requires no training, and naturally generalizes to unknown interference. A direct comparison would therefore be inappropriate, as it would evaluate a closed-set method on an open-set task for which it was not designed.

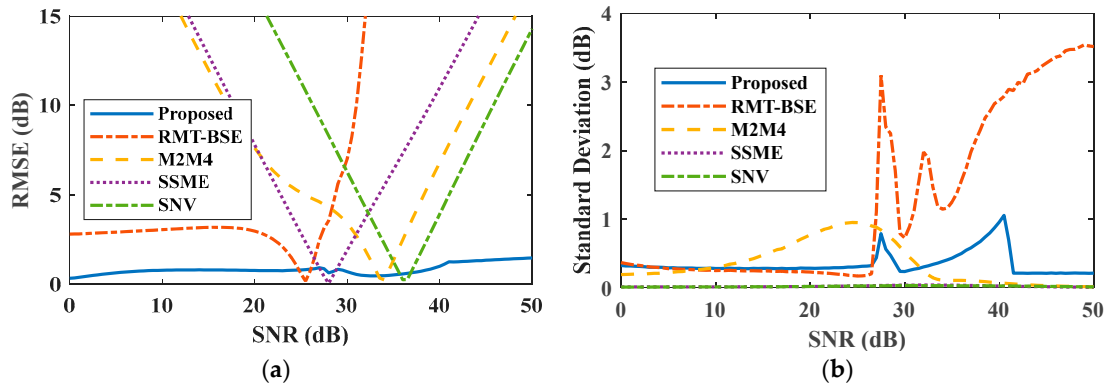


Figure 6. Performance comparison of different SINR evaluation algorithms: (a) RMSE of SINR estimation as a function of SNR; (b) STD of SINR estimation as a function of SNR.

Table 3. Mainstream algorithm comparison results.

Algorithm	RMSE (dB)	STD (dB)	BIAS (dB)
Proposed	0.83	0.34	0.71
RMT-BSE	11.34	1.24	11.24
M2M4	10.96	0.35	10.94
SSME	12.35	0.02	12.35
SNV	15.23	0.02	15.23

5.6. Computational Complexity and Execution Latency Analysis

To assess the feasibility of the proposed algorithm for real-time anti-jamming applications, this section provides a detailed analysis of its computational complexity and execution latency. The algorithm consists of four consecutive processing modules. We analyze the floating-point operation (FLOP) count of each module with respect to the number of array elements M , the number of snapshots K , and the estimated number of sources $\hat{D}$.

Module 1: Source number and noise power estimation (Section 4.2). This module first computes the sample covariance matrix $\hat{\mathbf{R}}$ from K snapshots, which requires $O(M^2K)$ FLOPs. An eigenvalue decomposition (EVD) of the $M \times M$ matrix $\hat{\mathbf{R}}$ is then performed, costing $O(M^3)$. The subsequent iterative refinement of the noise power estimate involves only averaging the noise-subspace eigenvalues and threshold updating, each iteration requiring $O(M)$ operations.

Module 2: Coarse desired-signal power estimation (Section 4.3). This module computes the normalized correlation coefficient between the a priori steering vector $\hat{\mathbf{a}}(\theta_0)$ and each of the $\hat{D}$ signal-subspace eigenvectors. Each correlation coefficient involves an inner product of two M -dimensional vectors, requiring $O(M)$ FLOPs. Hence, computing all $\hat{D}$ coefficients costs $O(M\hat{D})$. The subsequent eigenvalue identification and coarse power calculation involve only scalar operations of $O(1)$.

Module 3: Adaptive diagonal loading and robust Capon refinement (Sections 4.4 and 4.5). The closed-form diagonal loading factor (Equation (53)) is obtained directly from $\hat{\lambda}_s$,

the mismatch bound and the number of array elements, requiring $O(1)$ operations. The robust Capon power estimate (Equation (55)) can be efficiently computed using the EVD of $\hat{\mathbf{R}}$ already available from Module 1. Specifically, by projecting the steering vector onto the eigenvector basis and summing the weighted squared coefficients, the computation $\hat{\mathbf{a}}^H(\theta_0) \mathbf{R}_{\text{robust}}^{-1} \hat{\mathbf{a}}(\theta_0) = \sum_{m=1}^M |z_m|^2 / (\hat{\lambda}_m + \xi_{\text{opt}})$ requires $O(M^2)$ FLOPs, which is far cheaper than a direct matrix inversion.

Module 4: Interference power decoupling and SINR calculation (Section 4.5). The total received power $\text{tr}(\hat{\mathbf{R}})$ can be obtained as a by-product of covariance matrix formation. The interference power is then obtained via scalar subtractions, costing only $O(1)$ operations. A summary of the complexity of each module is provided in Table 4.

Table 4. Computational complexity of the proposed algorithm by module.

Algorithm	Complexity	Dominant Operations
Source number & noise power estimation	$O(M^3 + M^2K)$	Covariance formation, EVD
Coarse desired-signal power estimation	$O(M\hat{D})$	Steering-eigenvector correlations
Adaptive loading & Capon refinement	$O(M^2)$	Projection and summation (EVD already available)
Interference power decoupling	$O(1)$	Scalar arithmetic
Total	$O(M^3 + M^2K)$	/

From Table 4, the overall computational complexity of the proposed algorithm is $O(M^3 + M^2K)$. In typical anti-jamming applications, the number of snapshots K is often of the same order as or moderately larger than M . The cubic term $O(M^3)$ due to the EVD is usually the dominant cost when M is moderate, whereas for very large M and large K , the $O(M^2K)$ term from covariance formation may become comparable. It is worth noting that the complexity added by the proposed matching, loading, and refinement modules is only a small fraction of the total cost, meaning that the enhanced robustness does not come at the expense of a significant computational penalty.

To further validate real-time feasibility, we measured the average wall-clock execution time of the proposed algorithm under the simulation configuration of Table 1 with $M = 10$ and $K = 100$. The measurements were performed on a standard desktop computer (AMD Ryzen 7 5800H, 32 GB RAM, MATLAB R2024a). The average execution time per SINR estimate was 0.0212 ms. This confirms that the algorithm is suitable for real-time deployment.

5.7. Sensitivity to DOA Estimation Error

In practical engineering scenarios, the DOA of the desired signal is usually obtained by a preprocessing direction-finding module, which inevitably introduces estimation errors. DOA estimation errors directly cause steering vector mismatch, which further aggravates the signal self-cancellation effect in Capon power estimation and degrades SINR estimation performance. Therefore, it is necessary to quantitatively analyze the impact of DOA estimation errors on the proposed algorithm to verify its robustness in practical application scenarios. In this section, the nominal DOA of the desired signal is set as 0° , and DOA estimation errors ranging from 0° to 2° are introduced. The estimation performance under six typical SNR levels (from 0 dB to 50 dB) is tested. Two comparative scenarios are

set: (a) only DOA estimation error exists, without additional array amplitude-phase error; (b) both DOA estimation error and inherent array amplitude-phase mismatch exist (the mismatch model is consistent with previous sections, with error variance $\sigma_e^2 = 0.01$), to investigate performance degradation under compound mismatch conditions.

Figure 7b shows the estimation performance when DOA estimation error coexists with array amplitude-phase mismatch. Compared with Figure 7a, the overall variation trend of RMSE with DOA error and SNR remains consistent: the estimation error increases with the enlargement of DOA deviation, and the degradation is more serious at higher SNR. Due to the superposition of inherent array amplitude-phase errors, the overall RMSE level is slightly higher than that in the scenario with only DOA error. However, when the DOA error is no more than 0.5° , the algorithm can still control the RMSE at about 1 dB, which verifies that the proposed adaptive diagonal loading mechanism has favorable robustness to compound mismatch scenarios. In practical applications, array amplitude-phase error and DOA estimation error usually exist simultaneously. The results in this section show that within the typical engineering error range (DOA estimation error $\leq 1^\circ$), the proposed algorithm can maintain high estimation accuracy, which meets the requirements of practical anti-jamming systems.

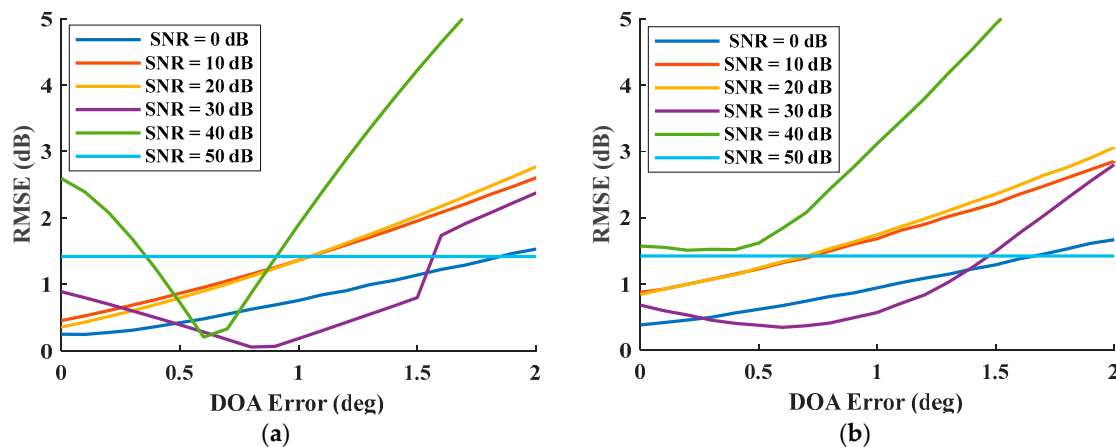


Figure 7. Sensitivity of SINR estimation RMSE to DOA estimation error: (a) ideal steering vector without mismatch ($\sigma_e^2 = 0$); (b) with steering vector mismatch ($\sigma_e^2 = 0.01$). Each curve corresponds to a fixed SNR level.

In summary, DOA estimation error is an important factor affecting SINR estimation performance, and the algorithm is more sensitive to DOA deviation under high-SNR conditions. The adaptive diagonal loading mechanism proposed in this paper can effectively compensate for small-amplitude DOA deviation and compound mismatch and maintain excellent estimation performance within the typical engineering error range, which proves the good engineering practicability of the algorithm.

5.8. Sensitivity to Array Size

To evaluate the influence of the array aperture, the number of elements M was varied from 6 to 20 in steps of 2 under the baseline configuration of Table 1. The SNR was fixed at 0, 10, 20, 30, 40, and 50 dB, while the steering vector mismatch variance was kept at $\sigma_e^2 = 0.01$ and the DOA estimation error was set to zero. For each SNR level, the RMSE of the SINR estimate was evaluated across the entire M range.

Figure 8 presents the variation trend of estimation RMSE with array size. Overall, the algorithm maintains stable performance across all tested configurations, with RMSE controlled within 2 dB. As M increases from 6 to 10, the RMSE decreases significantly under

most SNR conditions, since the expanded array aperture improves spatial resolution and mitigates eigenvalue coupling in the signal subspace, thus enhancing estimation accuracy.

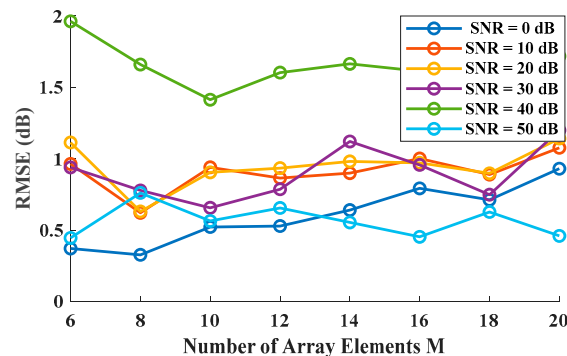


Figure 8. RMSE of SINR estimation versus the number of array elements M under different SNR conditions.

When M further rises to 20, the RMSE fluctuates slightly in a narrow range instead of continuing to decrease. This results from the trade-off between two competing effects: larger aperture brings potential spatial resolution gain, while limited snapshots cause larger estimation error of the sample covariance matrix, and the negative impact of steering vector mismatch on Capon estimation is gradually amplified. The two effects offset each other and keep the overall performance stable.

Consistent with previous conclusions, high-SNR scenarios have slightly higher RMSE due to more severe signal self-cancellation. Even for 6-element small arrays, the algorithm still achieves acceptable accuracy without severe degradation, verifying its good scalability for platforms with limited array size.

6. Conclusions

To address the limitations of conventional SINR estimation methods in non-cooperative strong interference environments, this paper proposes an adaptive robust SINR estimation algorithm based on spatial domain decoupling. The algorithm introduces the MP law for iterative source number and noise power estimation, constructs a progressive architecture consisting of eigen subspace-based coarse estimation and robust Capon-based fine estimation, and designs an adaptive strategy switching mechanism and an optimal diagonal loading mechanism. The proposed algorithm is independent of signal modulation types and is applicable to both constant-modulus and non-constant-modulus signals. Simulation results demonstrate that the algorithm maintains high estimation accuracy under strong interference, steering vector mismatch, and finite snapshot conditions, with an average RMSE of only 0.83 dB. It also exhibits a wider spatial applicability boundary and can effectively counter non-cooperative interference. Future work will further optimize the algorithm for engineering scenarios such as wideband signals and array non-ideal characteristics.

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Appendix A

The following proof shows that $d\|\mathbf{w}_L\|^2/d\xi < 0$ holds for all $\xi \geq 0$. Let

$$N(\xi) = \sum_{m=1}^M \frac{|z_m|^2}{(\hat{\lambda}_m + \xi)^2}, \quad D(\xi) = \sum_{m=1}^M \frac{|z_m|^2}{\hat{\lambda}_m + \xi}. \quad (\text{A1})$$

Then, $\|\mathbf{w}_L\|^2 = N/D^2$. Differentiating both sides with respect to ξ yields:

$$\frac{d\|\mathbf{w}_L\|^2}{d\xi} = \frac{N'D - 2ND'}{D^3}. \quad (\text{A2})$$

We can obtain:

$$N'(\xi) = -2 \sum_{m=1}^M \frac{|z_m|^2}{(\hat{\lambda}_m + \xi)^3}, \quad D'(\xi) = - \sum_{m=1}^M \frac{|z_m|^2}{(\hat{\lambda}_m + \xi)^2} = -N(\xi). \quad (\text{A3})$$

Substituting Equation (A3) into the numerator of Equation (A2) yields:

$$N'D - 2ND' = -2 \left(\sum_{m=1}^M \frac{|z_m|^2}{(\hat{\lambda}_m + \xi)^3} \right) \left(\sum_{m=1}^M \frac{|z_m|^2}{\hat{\lambda}_m + \xi} \right) + 2 \left(\sum_{m=1}^M \frac{|z_m|^2}{(\hat{\lambda}_m + \xi)^2} \right)^2. \quad (\text{A4})$$

We define:

$$\alpha_m = \frac{|z_m|}{(\hat{\lambda}_m + \xi)^{3/2}}, \quad \beta_m = \frac{|z_m|}{(\hat{\lambda}_m + \xi)^{1/2}}, \quad m = 1, \dots, M. \quad (\text{A5})$$

We have $\sum_{m=1}^M \alpha_m^2 = \sum_{m=1}^M \frac{|z_m|^2}{(\hat{\lambda}_m + \xi)^3}$, $\sum_{m=1}^M \beta_m^2 = \sum_{m=1}^M \frac{|z_m|^2}{(\hat{\lambda}_m + \xi)}$, and $\sum_{m=1}^M \alpha_m \beta_m = \sum_{m=1}^M \frac{|z_m|^2}{(\hat{\lambda}_m + \xi)^2}$. By

the Cauchy–Schwarz inequality, it follows that:

$$\left(\sum_{m=1}^M \alpha_m \beta_m \right)^2 \leq \left(\sum_{m=1}^M \alpha_m^2 \right) \left(\sum_{m=1}^M \beta_m^2 \right). \quad (\text{A6})$$

Equality holds if and only if there exists a constant p such that $\alpha_m = p \cdot \beta_m$ for all m , that is,

$$\frac{|z_m|}{(\hat{\lambda}_m + \xi)^{3/2}} = p \cdot \frac{|z_m|}{(\hat{\lambda}_m + \xi)^{1/2}} \Rightarrow \frac{1}{\hat{\lambda}_m + \xi} = p. \quad (\text{A7})$$

This implies that all eigenvalues are identical, i.e., $\lambda_1 = \lambda_2 = \dots = \lambda_M$. In practical array reception scenarios, where both signal sources and noise exist, the eigenvalues of the covariance matrix cannot be entirely equal. Hence, the above inequality holds strictly. Therefore:

$$\left(\sum_{m=1}^M \frac{|z_m|^2}{(\hat{\lambda}_m + \xi)^2} \right)^2 < \left(\sum_{m=1}^M \frac{|z_m|^2}{(\hat{\lambda}_m + \xi)^3} \right) \left(\sum_{m=1}^M \frac{|z_m|^2}{\hat{\lambda}_m + \xi} \right). \quad (\text{A8})$$

Substituting Equation (A8) into (A4) shows that the numerator is always negative. Since the denominator $D^3 > 0$, it follows that:

$$\frac{d \|\mathbf{w}_L\|^2}{d\xi} < 0, \quad \forall \xi \geq 0. \quad (\text{A9})$$

Since $\|\mathbf{w}_L\| = \sqrt{\|\mathbf{w}_L\|^2}$ and the square root function is monotonically increasing, it follows that $\|\mathbf{w}_L(\xi)\|$ is strictly decreasing on $\xi \in [0, \infty)$.

Appendix B

The analysis in Section 3.2.2 establishes the maximum-correlation matching criterion under a single-interference model. This appendix provides a rigorous extension to the general case with Q mutually independent far-field interferers.

Consider one desired signal and Q interferers. The total number of sources is $D = Q + 1$. The array covariance matrix is

$$\mathbf{R} = \sigma_s^2 \mathbf{a}(\theta_0) \mathbf{a}^H(\theta_0) + \sum_{q=1}^Q \sigma_{j,q}^2 \mathbf{a}(\theta_q) \mathbf{a}^H(\theta_q) + \sigma_n^2 \mathbf{I}_M. \quad (\text{A10})$$

Let $\mathbf{A}_J = [\mathbf{a}(\theta_1), \dots, \mathbf{a}(\theta_Q)]$ and $\mathbf{\Sigma}_J = \text{diag}(\sigma_{j,1}^2, \dots, \sigma_{j,Q}^2)$. Define the normalized spatial correlation coefficient $\gamma_q = \frac{1}{M} \mathbf{a}^H(\theta_0) \mathbf{a}(\theta_q)$ and the total squared correlation

$$\mathcal{E} \triangleq \sum_{q=1}^Q |\gamma_q|^2. \quad (\text{A11})$$

In non-cooperative scenarios, jammers are typically well separated in angle from the desired transmitter, so $\mathcal{E} \ll 1$.

Rewrite the covariance matrix as a rank-one update of the interference-plus-noise component:

$$\mathbf{R} = \mathbf{R}_{Jn} + \sigma_s^2 \mathbf{a}(\theta_0) \mathbf{a}^H(\theta_0), \quad \mathbf{R}_{Jn} \triangleq \mathbf{A}_J \mathbf{\Sigma}_J \mathbf{A}_J^H + \sigma_n^2 \mathbf{I}_M. \quad (\text{A12})$$

Let $\mathbf{v}_0 = \mathbf{a}(\theta_0)/\sqrt{M}$ be the normalized desired steering vector. We assume the following physically reasonable conditions hold:

- (a) Low spatial correlation: $\mathcal{E} \leq \mathcal{E}_0 < 1$.
- (b) Moderate signal-to-total-interference ratio: $\sigma_s^2 \geq \delta \sigma_{J,\text{tot}}^2$ for some $\delta > 0$, where

$$\sigma_{J,\text{tot}}^2 = \sum_{q=1}^Q \sigma_{j,q}^2.$$

Let $\mathbf{u}_{\text{sig}}$ be the eigenvector of $\mathbf{R}$ corresponding to the eigenvalue dominated by the desired signal. Decompose $\mathbf{u}_{\text{sig}}$ along $\mathbf{v}_0$ and its orthogonal complement:

$$\mathbf{u}_{\text{sig}} = \alpha \mathbf{v}_0 + \beta \mathbf{w}, \quad |\alpha|^2 + |\beta|^2 = 1, \quad \mathbf{w} \perp \mathbf{v}_0. \quad (\text{A13})$$

The correlation coefficient is $\rho_{\text{sig}} = |\alpha|$. Since the Rayleigh quotient of an eigenvector equals its eigenvalue and is maximal, we have:

$$\mathbf{v}_0^H \mathbf{R} \mathbf{v}_0 \leq \lambda_{\text{sig}} = \mathbf{u}_{\text{sig}}^H \mathbf{R} \mathbf{u}_{\text{sig}}. \quad (\text{A14})$$

Expanding the right-hand side using (A13) and noting $\mathbf{w}^H \mathbf{R} \mathbf{w} \leq \lambda_{\text{max}}(\mathbf{R}_{J_n})$, we obtain after rearrangement:

$$(1 - |\alpha|^2)(\mathbf{v}_0^H \mathbf{R} \mathbf{v}_0 - \lambda_{\text{max}}(\mathbf{R}_{J_n})) \leq 2\sqrt{1 - |\alpha|^2} \|\mathbf{R}_{J_n} \mathbf{v}_0\|. \quad (\text{A15})$$

Dividing by $\sqrt{1 - |\alpha|^2}$ (the case $|\alpha| = 1$ is trivial) yields:

$$\sqrt{1 - \rho_{\text{sig}}^2} \leq \frac{2\|\mathbf{R}_{J_n} \mathbf{v}_0\|}{\mathbf{v}_0^H \mathbf{R} \mathbf{v}_0 - \lambda_{\text{max}}(\mathbf{R}_{J_n})}. \quad (\text{A16})$$

To bound the numerator, we compute:

$$\mathbf{R}_{J_n} \mathbf{v}_0 = \sum_{q=1}^Q \sigma_{j,q}^2 \mathbf{a}(\theta_q) (\mathbf{a}^H(\theta_q) \mathbf{v}_0) + \sigma_n^2 \mathbf{v}_0, \quad (\text{A17})$$

$$\|\mathbf{R}_{J_n} \mathbf{v}_0\| \leq M \sum_{q=1}^Q \sigma_{j,q}^2 |\gamma_q| + \sigma_n^2 \leq M \sigma_{J,\text{tot}}^2 \sqrt{\varepsilon} + \sigma_n^2. \quad (\text{A18})$$

For the denominator, we have:

$$\mathbf{v}_0^H \mathbf{R} \mathbf{v}_0 = M \sigma_s^2 + \mathbf{v}_0^H \mathbf{R}_{J_n} \mathbf{v}_0 \geq M \sigma_s^2 + \sigma_n^2, \quad (\text{A19})$$

and $\lambda_{\text{max}}(\mathbf{R}_{J_n}) \leq \sigma_n^2 + M \sigma_{J,\text{tot}}^2$. Hence, we have:

$$\mathbf{v}_0^H \mathbf{R} \mathbf{v}_0 - \lambda_{\text{max}}(\mathbf{R}_{J_n}) \geq M(\sigma_s^2 - \sigma_{J,\text{tot}}^2). \quad (\text{A20})$$

Substituting (A18) and (A20) into (A16) gives:

$$\sqrt{1 - \rho_{\text{sig}}^2} \leq \frac{2(M \sigma_{J,\text{tot}}^2 \sqrt{\varepsilon} + \sigma_n^2)}{M(\sigma_s^2 - \sigma_{J,\text{tot}}^2)}. \quad (\text{A21})$$

Under the low-correlation and moderate-power assumptions, the numerator is dominated by $O(\sqrt{\varepsilon})$ while the denominator remains on the order of $M \sigma_s^2$. Consequently, $1 - \rho_{\text{sig}}^2 = O(\varepsilon)$, i.e., the following:

$$\rho_{\text{sig}} \geq 1 - O(\varepsilon). \quad (\text{A22})$$

The projection energy of $\mathbf{a}(\theta_0)$ onto the signal subspace is conserved:

$$\sum_{i=1}^D \rho_i^2 = \frac{1}{M} \|\mathbf{U}_s^H \mathbf{a}(\theta_0)\|^2 = 1 - \delta_{\text{noise}}, \quad (\text{A23})$$

where δ_{noise} is the negligible fraction leaking into the noise subspace. Since ρ_{sig}^2 already accounts for a share of $1 - O(\varepsilon)$, the remaining $D - 1$ eigenvectors collectively contribute at most $O(\varepsilon) + \delta_{\text{noise}}$. Therefore, $\rho_j < \rho_{\text{sig}}$ for all $j \neq \text{sig}$.

This completes the rigorous justification: under the practically relevant conditions of low spatial correlation and non-negligible desired signal power, the eigenvector achieving the maximum normalized correlation with the prior steering vector $\hat{\mathbf{a}}(\theta_0)$ is exactly the one dominated by the desired signal. The maximum-correlation matching criterion adopted in Section 4.3 is therefore rigorously valid for an arbitrary number of interferers.

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