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An Adaptive Diagonal Loading Technique to Improve Direction of Arrival Estimation Accuracy for Linear Antenna Array Sensors

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***Abstract*—Diagonal loading is one of the most widely used and effective methods to improve the robustness of both adaptive beamformers and Direction of Arrival (DOA) estimation due to the involvement of the sensor received covariance matrix. In addition, subspace-based DOA estimation techniques rely on multiple snapshots to achieve high estimation accuracies. This paper presents the study of a modified diagonally loaded sample covariance matrix for accurate DOA estimation in adverse scenarios. The proposed and novel technique deciphers poor DOA estimation in a low SNR environment by computationally changing the received sample covariance matrix. Our method is computationally simple as it does not require peak searching and does not depend on the coherency of the signal. The efficacy of the proposed method is examined via computer simulation for various sensor array sizes and the number of snapshot samples. Based on our numerical simulation results, our proposed method generally outperforms most state-of-the-art DOA estimators. In a finite number of snapshots and a single signal source, our proposed method performs 9.5% better than the state-of-the-art DOA estimation technique, 2.8% in multiple signal sources, and 8.5% in a single snapshot, single signal source environment of gained DOA estimation performance.**

***Index Terms*—Antenna arrays, DOA Estimation, Sensor Applications**

I. Introduction

DIRECTION of Arrival (DOA) estimation is one of the most critical topics in sensor array signal processing with applications such as radar [1], localization & tracking [2], and wireless vehicular communications [3]. Many DOA estimation techniques have been proposed in the past, such as the classical Multiple Signal Classification (MUSIC) [4] and its modified variants [5-7]. These techniques use the decomposition of the sample covariance matrix to determine the signal and noise subspaces to determine the DOAs. Alternatively, newer techniques such as implementing Machine-Learning (ML) and Information Geometry (IG) have recently been in active research for DOA estimation. In [8], an ML-based DOA estimator was proposed for vehicular applications, which yields excellent estimation accuracy. In [9], the implementation of IG with DOA estimation was conducted by exploiting the relationship between probability density and the differential geometry structure of the received data and geodesic distance. This IG technique, known as Scaling Transform-based Information Geometry (STRING), resulted in higher accuracy and DOA estimation resolution.

However, these existing techniques have some significant drawbacks. First, these techniques yield high computational complexities and are impractical for real-world applications that differ in various environments. For example, a sensor array can be developed based on a 5500 MHz operating frequency band but loses signal and estimation performance when operating in other frequency bands [10]. In addition, ML-based techniques require elaborate and comprehensive offline data training for optimization and operational efficiency. Moreover, although the IG-based technique presents good DOA estimation accuracy, but has significant statistical bias and results in poor robustness, especially at a high Signal-to-Noise Ratio (SNR).

In more recent years, numerous state-of-the-art DOA estimation techniques have been proposed with increased estimation accuracy and robustness. In [11], a novel enhanced principal-singular-vector utilization for modal analysis (EPUMA) DOA estimation approach was proposed. The EPUMA technique provides reliable performance when the number of snapshot samples is small, even when the number of samples is lower than the number of impinging signals. The simulation results in [11] indicates that the EPUMA approach outperforms many other subspaced-based DOA estimators, especially for small sample scenarios. In [12], an Eigenvalue-based DOA estimator named the Partial-Relaxation (PR)

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approach was proposed. The PR approach is based on the deterministic maximum likelihood, weighted subspace fitting, and covariance fitting methods. By using an iterative rooting scheme based on the rational function approximation, the DOA is determined by first relaxing the manifold structure of the remaining interfering signals that results in a closed form estimation. Then, DOA is approximated by using a simplified peak spectral search. The simulation results of [12] shows tha, irrespective of any structure of the sensor array, the performance of the PR approach is superior to the conventional methods in low SNR and snapshots while maintaining comparable computational costs to MUSIC.

A simple technique to reduce complexities is by reducing the number of snapshots required for DOA estimation, where less data processing is required for an algorithm to determine the covariance matrix. There have been many attempts in using a single snapshot for DOA estimation. In [13], a low complex single snapshot DOA estimation was proposed. This technique was conducted by first obtaining rough initial DOA estimates and then searching for accurate estimates within a very small region. The proposed approach offered high accuracy with low complexity but required many antenna array elements for best performance. Alternatively, [14] presented a novel approach for recursively estimating the DOAs as measurements based on worst-case gain minimization to reduce estimation error with a single snapshot. The simulations in [14] presented good DOA estimation results but required significantly high SNR levels of up to 35 dB, which is impractical in real-world scenarios.

In more recent years, Diagonal Loading (DL) of the sample covariance matrix has been a popular technique to improve DOA estimation efficacy and beamforming capabilities while reducing computational costs in a limited sample situation [15, 16]. The DL algorithms can be considered an auxiliary subsystem into the primary DOA technique by correcting all the sample eigenvalues with the same parametric value to increase the resolution for improved beamforming and signal direction selection [17]. In [3], a DOA estimation method was proposed by integrating a modified orthogonal propagator technique with spline interpolation, a form of DL. This was carried out by restoring the noise-free diagonal elements through an interpolation procedure while the propagator can then be directly extracted from the denoised sample covariance matrix. The proposed method offers a unique approach to reducing the noise impact. However, this method is solely based on the pseudo-spectrum DOA estimation technique, which is still considered computationally expensive with an inherently slow DOA estimation detection. The complexity of their proposed approach increases exponentially as the number of signal sources increases and only presents good estimation in a significantly high SNR environment and presents weaker estimation performance in low SNR of < 0 dB. In addition, operating frequency mismatch was not taken into consideration in the development of their proposed technique.

In another example, [18] presented a similar DL-based approach – a quadratically constrained beamformer that is robust against DOA mismatch. A DL method was used to force magnitude responses at the arrival angles between two steering vectors that exceed unity in the pseudo-spectrum. This method causes the gains at a desired range of angles to exceed a constant level while suppressing the interferences and noise with numerical results that have excellent estimation performance. However, the critical drawback of the proposed technique in [18] is that the complexity depends on the number of iterations wholly dependent on the SNR. The higher the SNR, the higher the iteration, which leads to higher computational costs. Furthermore, there is an additional iteration that was not mentioned. The condition given in the paper is based on granular angle values (i.e., $0°, 30°, 80°$). The computational complexity increases exponentially when a high-resolution estimation is required.

To that end, this paper aims to develop an adaptive DL-based technique for DOA estimation applied to the sample covariance matrix to achieve high estimation accuracy for a wide range of operating frequencies and SNR without the need for increased computational complexity. Achieving a holistically predictable and accurate DOA estimator model complements multiple sensors applications regardless of the antenna sensor geometry and use-cases. Our proposed DL technique consists of an effective but straightforward adaptive DL estimator based on the steering vector's error rate of change and changes in estimation parameters such as operating frequencies for a fixed antenna array sensor position. According to our simulation results, our proposed method generally outperforms all other DOA estimators. Our proposed method performs 9.5% better than the state-of-the-art EPUMA [11] technique in a finite number of snapshots and a single signal source. In a scenario where there are multiple signals of interest, our proposed method performs 2.8% better than EPUMA and up to 5% at higher SNR of > 0 dB. In a single snapshot sample with a single signal source of interest, our proposed method performs 8.5% better than EPUMA and is significantly closer to the Cramer-Rao Bound (CRB) limit when compared to the other demonstrated DOA estimators.

The fundamental characteristic of our proposed method enables DOA estimation in many applications with cost, size, and hardware limitations and considerations, such as in the field of transportation and vehicular signal localization and high-bandwidth connectivity, especially in the current uprising trend of wireless communication. This is done by modifying the pre-processing DOA estimation section that can be applied to any form of DOA estimators. Specifically, we propose a pre-processing covariance matrix reconstruction using a modified DL technique that enables and boost estimation accuracy, especially in a low SNR environment. Ultimately, we want to achieve a linear bias value across a wide range of SNR scenarios to obtain stable and predictable DOA estimation.

The remainder of this paper is organized as follows. Section II presents the system model for an antenna array and the derivation of the received signal covariance matrix. Section III offers our proposed pre-processing technique. Section IV presents the simulation results and discussion demonstrating the performance of our proposed method in varying antenna array element sizes with its Root Mean Squared Error (RMSE) and bias, as well as a quantitative analysis of our proposed method in an exhausted single snapshot scenario. Finally, Section V concludes the paper.

II. Problem Formulation & Data Model

The problem formulation and data model are assumed and maintained through the description of the problem formulation and, subsequently, the data model of this paper. Firstly, the received signal model is described. Then, the standard diagonal loading technique is explained.

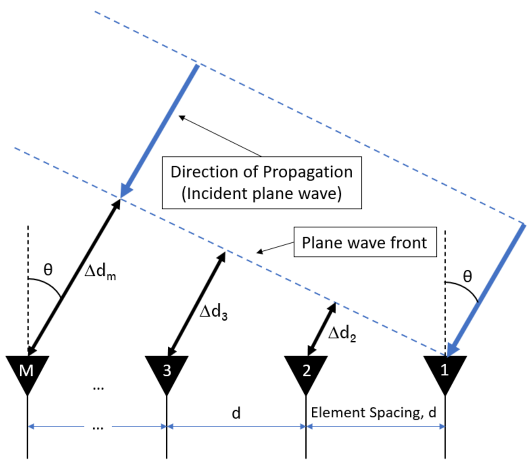

Figure 1: Sensor Array Model

A. Received Signal Model & Sensor Data Correlation Matrix

With reference to Fig. 1, consider an array of M sensors receiving the signals emitted by L narrowband far-field sources with unknown DOAs $\{\theta_1, \ \ldots, \ \theta_L\}$ with inter-element spacing d being no greater than $\lambda/2$. The number of L incident signals is assumed to be available where the wavelength of incident signals, $\lambda = c/f$, where f is the signal carrier frequency and c is the speed of light in a vacuum. The k^{th} array snapshot of the received signal is expressed as [1]-[2]

$$\mathbf{x}(k) = \mathbf{A}\mathbf{s}(k) + \mathbf{n}(k), \tag{1}$$

where $\mathbf{A} = [\mathbf{a}(\theta_1), \mathbf{a}(\theta_2), \cdots, \mathbf{a}(\theta_L)]$ denotes the steering matrix, and $\mathbf{a}(\theta) = [a_1(\theta), a_2(\theta), \cdots, a_M(\theta)]^T$ is the steering vector whose m^{th} entry is given by

$$a_m(\theta) = e^{jf_m(\theta)}, \tag{2}$$

where $f_m(\theta)$ is a known operating frequency function with respect to θ for given coordinates of the m^{th} sensor and j is a complex number and $-90 \geq \theta < 90$ with half-wavelength ULA with inter-element spacing, where $f_m(\theta) = \pi(m - 1)\sin\ \theta$.

In (1), $\mathbf{s}(k) = [s_1(k), s_2(k) \ldots, s_L(k)]^T$ and $\mathbf{n}(k) = [n_1(k), n_2(k), \cdots, n_M(k)]^T$ denote the signal and noise vectors, respectively which are assumed to be uncorrelated. The noise parameter $\mathbf{n}(k)$ is considered to be zero-mean with variance $\sigma^2\mathbf{I_M}$ white Gaussian noise vector independent of $\mathbf{s}(k)$ while $\mathbf{I_M}$ is an $M \times M$ identity matrix. Then, we define the theoretical array covariance matrix as [1]-[2]

$$\mathbf{R_{xx}} = \mathbb{E}\{\mathbf{x}(k)\mathbf{x}^{\text{H}}(k)\} = \mathbf{A}\mathbf{E}_{\text{s}}\mathbf{A}^{\text{H}} + \mathbf{E}_{\text{N}}, \tag{3}$$

where $\mathbf{R_{xx}}$ is the theoretical covariance matrix of size $M \times M$ while $\mathbb{E}\{\cdot\}$ and $(\cdot)^{\text{H}}$ represents the mathematical expectation and Hermitian transpose, respectively while $\mathbf{E}_{\text{s}} = \mathbb{E}\{\mathbf{s}(k)\mathbf{s}^{\text{H}}(k)\}$ is the signal subspace, and $\mathbf{E}_{\text{N}} = \mathbb{E}\{\mathbf{n}(k)\mathbf{n}^{\text{H}}(k)\}$ is the noise subspace.

In practice, however, the exact covariance matrix of $\mathbf{R_{xx}}$ is challenging to obtain due to the limited number of data sets received and processed by a sensor array system. Thus, an estimation is made using limited, finite snapshot samples in an instantaneous time to overcome this limitation. Assuming that all underlying random noise processes are ergodic, the statistical expectation in (3) can be replaced by a time average. An estimate of the data covariance matrix $\mathbf{R_{xx}}$ can be presented as a sample covariance matrix, which is expressed as

$$\mathbf{R_{xx}} \approx \widehat{\mathbf{R}}_{\mathbf{xx}} = \frac{1}{K}\sum_{k=1}^{K} \mathbf{x}(\text{k})\mathbf{x}^{\text{H}}(\text{k}) = \frac{1}{K}\mathbf{X}\mathbf{X}^{\text{H}}, \tag{4}$$

where $\widehat{\mathbf{R}}_{\mathbf{xx}}$ is the sample covariance matrix, $\mathbf{X}$ is the input data matrix of size $M \times K$, and K is the number of snapshot samples.

B. Diagonal Loading

One of the easiest and most efficient methods to improve robustness against DOA mismatch and ensure the complete rank structure is to add constant values with the diagonal elements of the received signal correlation matrix. This is known as the fixed-diagonal loading method [15]. The diagonal loading technique is also commended for its effectiveness in handling various errors, including steering vector estimation and finite-sample errors. In addition, it can equalize the least significant eigenvalues of the covariance matrix or constrain the white noise gain. One of the inherent drawbacks of using DL is that it induces considerable bias. However, this can be overcome by using bias correction [17] before parsing the final DOA. To that end, the diagonally loaded covariance matrix is defined as [10]

$$\mathbf{R_{xx-DL}} = \mathbb{E}\{\mathbf{X}\mathbf{X}^{\text{H}}\} + F\mathbf{I}, \tag{5}$$

where $\mathbf{I}$ is an identity matrix of size $M \times M$.

The scalar parameter of F denotes the amount of diagonal loading into the covariance matrix. Therefore, assuming that $F = 0$, no diagonal loading is present. In other words, it uses the standard covariance matrix as shown in (4). Note that F can be positive or negative, but F must be greater than $-\sigma^2$ for the covariance matrix to be positive definite. In addition, values of F close to $-\sigma^2$ must be avoided to ensure numerical stability.

Similarly, the additive diagonal loading in (5) can also be demonstrated to the sample covariance matrix in (4), which is given as [11]

$$\widehat{\mathbf{R}}_{\mathbf{xx}} = \frac{1}{\text{K}}\mathbf{X}\mathbf{X}^{\text{H}} + \ F\mathbf{I}. \tag{6}$$

Before computing the weight vector, a diagonally loaded matrix is added to the sample covariance matrix in (6). This technique strengthens the noise components, which results in the input SNR reduction and suppression of the disturbance of small eigenvalues corresponding to the noise subspace. F should be a large enough value to reduce the input SNR. However, the interference component proportion also decreases, which reduces null depth in a pseudo-spectrum. Therefore, F should also be small enough to prevent the decline in null depth. There is always a trade-off between robustness, interference cancellation, and noise reduction. For example, for large F, the robustness against mismatch and replacement increases while interference cancellation and noise reduction capabilities decrease. Alternatively, for small F, the robustness is diminished. Therefore, the diagonal loading value should be appropriately selected to achieve performance improvement in a DOA estimation system.

A key benefit of diagonal loading is to overcome the inversion of the sample covariance matrix. When the number of snapshots is small, $\mathrm{K} < \mathrm{L}$, the inverted covariance matrix is not full rank and thus irreversible. The practical robustness can be analyzed as follows. Let μ_l and $\mathbf{u}_l$ for $l = 1,2,\ldots,L$ be the subsequent eigenvalues and eigenvectors of $\widehat{\mathbf{R}}_{\mathbf{xx}}$, respectively. Then, with reference to (4), it can be further decomposed as [12]

$$\widehat{\mathbf{R}}_{\mathbf{xx}} = \sum_{l=1}^{L} \mu_l \, \mathbf{u}_l \mathbf{u}_l^{\mathrm{H}}, \tag{7}$$

which leads to the following decomposition,

$$\widehat{\mathbf{R}}_{\mathbf{xx}}^{-1} \mathbf{a}(\tilde{\theta}_0) = \sum_{l=1}^{L} \frac{\mathbf{u}_l^{H} \mathbf{a}(\tilde{\theta}_0)}{\mu_l} \mathbf{u}_l \,. \tag{8}$$

From (8), when μ_l is small, $\widehat{\mathbf{R}}_{\mathbf{xx}}^{-1}\mathbf{a}(\tilde{\theta}_0)$ tend towards a substantial value, leading to a high level of sidelobe errors and would result in the wrong signal direction of interest estimation. With the inclusion of diagonal loading, the decomposition becomes

$$(\widehat{\mathbf{R}}_{\mathbf{xx}} + F\mathbf{I}\,)^{-1} \mathbf{a}(\tilde{\theta}_0) = \sum_{l=1}^{L} \frac{\mathbf{u}_l^{\mathrm{H}} \mathbf{a}(\tilde{\theta}_0)}{\mu_l + F} \mathbf{u}_l. \tag{9}$$

From (9), adding the diagonal loading enables inversion to solve the available small sample size. Another benefit is that the sidelobes are suppressed for efficient beamforming in an intelligent antenna sensor system. Furthermore, adding the diagonal loading can reduce the influence of small eigenvalues; thereby, the weight vector norm is not amplified erratically. However, it is worth reiterating that this comes with a trade-off between the robustness and the expense in interference cancellation and noise reduction.

III. Proposed Traced Diagonal-Loading DOA Estimation Method

Although the diagonal-loading method, as shown in (9), shows promising results in a broad spectrum of SNR values, the technique still must process the entire covariance matrix, which may not even be of a Toeplitz structure, especially in a practical sample-based covariance matrix. In addition, selecting the correct loading factor remains crucial for accurate DOA estimation. Thus, the performance can vary significantly, and finding an optimal loading factor derivation remains a significant research interest.

This section shows how to reduce further and simplify the elements within the covariance matrix without sacrificing its accuracy. To illustrate our proposed technique, we first observe the structure of the covariance matrix from (3) as

$$\mathbf{R}_{\mathbf{xx}} = \begin{bmatrix} xx_{1\times 1} & \cdots & xx_{1\times m} \\ \vdots & \ddots & \vdots \\ xx_{m\times 1} & \cdots & xx_{m\times m} \end{bmatrix}. \tag{10}$$

We then proceed to partition the diagonal vector in $\mathbf{R}_{\mathbf{xx}}$ of interest and reformulate it as a vector as

$$\mathbf{r}_{\mathbf{xx-diag}} = [xx_{1\times 1} \quad \ldots \quad xx_{m\times m}]\,, \tag{11}$$

where $\mathbf{r}_{\mathbf{xx-diag}}$ is a vector of size $M \times 1$.

From (11), we reform and partition the vector, $\mathbf{r}_{\mathbf{xx-diag}}$, into a Toeplitz Hermitian matrix as

$$\mathbf{R}_{\mathbf{xx-reform}} = \begin{bmatrix} xx_{1\times 1} & \ldots & xx_{m\times m} \\ \vdots & \ddots & \vdots \\ xx_{m\times m} & \ldots & xx_{m\times m} \end{bmatrix}, \tag{12}$$

where $\mathbf{R}_{\mathbf{xx-reform}}$ is of size $M \times M$ similar to (10).

Note that the technique represented in (10) to (12) can be applied to the sample covariance matrix, $\widehat{\mathbf{R}}_{\mathbf{xx}}$. Comparing (10) and (12), the critical difference is that the off-diagonal elements replicate the elements along the diagonals for (12). One key advantage of this technique is that it reduces the computational load onto the system without calculating many different values of array elements.

Next, to determine a suitable F value for diagonal loading implementation, we define the following equation

$$F = \frac{1}{K} \|\beta^{\mathrm{H}} \mathbf{R}_{\mathbf{xx}}\|^2 \tag{13}$$

where $\beta = \mathbf{a}(\tilde{\theta}_0)/\|\mathbf{a}(\tilde{\theta}_0)\|$ is the normalized steering vector in the desired signal direction of interest. Note that this normalization does not change the primary direction of interest, only its magnitude. This idea removes the influence of low SNR impedance in any application or scenario. The trade-off of this technique is that although it will result in consistent bias, it does not necessarily mean that there will be negligible bias. The bias discrepancy will be demonstrated later in the simulation section.

It is seen in (13) that the loading level depends on the signal and noise power. Finally, combining (13) with (5) and (6), we obtain:

$$\mathbf{R}_{\mathbf{xx-DL-Mod}} = \mathbb{E}\{\mathbf{XX}^{\mathrm{H}}\} + \left[\frac{1}{\mathrm{K}}\|\beta^{\mathrm{H}}\mathbf{R}_{\mathbf{xx}}\|^2\right]\mathbf{I}, \tag{14}$$

$$\widehat{\mathbf{R}}_{\mathbf{xx-DL-Mod}} = \frac{1}{\mathrm{K}}\left\{\mathbf{XX}^{\mathrm{H}} + \left[\|\beta^{\mathrm{H}}\mathbf{R}_{\mathbf{xx}}\|^2\right]\mathbf{I}\right\}, \tag{15}$$

where (14) and (15) represent the theoretical and sample diagonally loaded tracing covariance matrix, respectively.

Lastly, before the decomposition to obtain the signal and noise subspace, and considering only the sampled covariance matrix, we modify the diagonally loaded covariance matrix as:

$$\widehat{\mathbf{R}}_{\mathbf{xx-DLT}} = \widehat{\mathbf{R}}_{\mathbf{xx-DL-Mod}} + \mathrm{tr}\big(\widehat{\mathbf{R}}_{\mathbf{xx-DL-Mod}}\big), \tag{16}$$

where $\mathrm{tr}(\cdot)$ is the trace of a matrix.

Fig. 2 presents the algorithmic flowchart summary of our proposed technique for the sample covariance matrix reformulation. After determining the first sample covariance matrix, $\widehat{\mathbf{R}}_{\mathbf{xx}}$ as in (4) from the incoming received signal data matrix, the diagonal elements are extracted and reformed into a new modified covariance matrix, $\mathbf{R}_{\mathbf{xx-reform}}$ like in (12). Concurrently, the diagonal loading factor, F, is calculated, which leads to the reformulation of a new diagonally loaded sample covariance matrix, $\widehat{\mathbf{R}}_{\mathbf{xx-DL-Mod}}$ as in (15). Finally, the traced sample covariance matrix, $\widehat{\mathbf{R}}_{\mathbf{xx-DLT}}$ is reformulated for DOA estimation as described in (16).

Then, the subspace decomposition of (16) can be presented as

$$\widehat{\mathbf{R}}_{\mathbf{xx-DLT}} = \mathbf{U}_s\mathbf{\Omega}_s\mathbf{V}_s^{\mathrm{H}} + \mathbf{U}_n\mathbf{\Omega}_n\mathbf{V}_n^{\mathrm{H}}, \tag{17}$$

where $\mathbf{U}_s$ and $\mathbf{V}_s$ span the column spaces of $\widehat{\mathbf{R}}_{\mathbf{xx-DLT}}$ and $\widehat{\mathbf{R}}_{\mathbf{xx-DLT}}{}^{\mathrm{H}}$ respectively, whereas $\mathbf{U}_n$ and $\mathbf{V}_n$ span their orthogonal spaces and $\mathbf{\Omega}_s$ and $\mathbf{\Omega}_n$ are the corresponding diagonal matrices with eigenvalues or singular values on the diagonal, respectively.

Algorithm 1 Covariance Matrix Reformulation using DLT Algorithm

Require: Incoming SNR Data Matrix from Sensor Array, $\mathbf{X}$

procedure DLT-RM(θ)
  Determine $\hat{\mathbf{R}}_{xx} = \frac{1}{K}\mathbf{XX^H}$
  Extract Diagonal Elements $Diag(\hat{\mathbf{R}}_{\mathbf{xx}})$ from $\hat{\mathbf{R}}_{\mathbf{xx}}$
  Restructure $Diag(\hat{\mathbf{R}}_{\mathbf{xx}})$ into $\hat{\mathbf{R}}_{\mathbf{xx-reform}}$
  while $\hat{\mathbf{R}}_{\mathbf{xx-reform}}$ is being determined **do**
    Calculate $F = \frac{1}{K}\|\beta^H\hat{\mathbf{R}}_{\mathbf{xx}}\|^2$
  end while
  Reconstruct $\hat{\mathbf{R}}_{\mathbf{DL-Mod}} = \frac{1}{K}\{\|\beta^{\mathbf{H}}\hat{\mathbf{R}}_{\mathbf{xx}}\|^2\}\mathbf{I}$
  Reformulate $\hat{\mathbf{R}}_{\mathbf{DLT}} = \hat{\mathbf{R}}_{\mathbf{DL-Mod}} + trace(\hat{\mathbf{R}}_{\mathbf{DL-Mod}})$
  Decompose Signal and Noise Subspace $\hat{\mathbf{R}}_{\mathbf{Decomp-DLT}} = \mathbf{U_s\Omega_s V_s}^{\mathbf{H}} + \mathbf{U_n\Omega_n V_n}^{\mathbf{H}}$
end procedure

Figure 2: Proposed Algorithm Flowchart

IV. Simulation Results & Discussion

In this section, numerical examples are provided to study the stochastic effectiveness of our proposed method, as formulated in section III. To illustrate, the value of F has an impact corresponding to the input SNR and Uniform Linear Array (ULA) with equally spaced half-wavelength geometry. The input SNR is varied to generate different $\widehat{\mathbf{R}}_{\mathbf{xx-DLT}}$ with zero-mean Additive White Gaussian Noise (AWGN) against varying SNR ranging from -10 dB to 10 dB. To further illustrate the efficiency of our proposed method, we present the simulation study in different scenarios. Firstly, in a scenario where there is a minimal finite snapshot availability. Next, we provide the estimation performance of our proposed technique where are multiple signal sources of interest. Lastly, we deliver the performance of our proposed method where only a single snapshot is available, which can be considered a worst-case scenario.

We compared our technique against state-of-the-art techniques such as the Enhanced Principal-eigenvector Utilization for Modal Analysis (EPUMA) [11], Method of Direction of Arrival Estimation (MODE) [19], MODEX [20], and root-MUSIC with Forward-backward Spatial Smoothing (FBSS) [21].

The simulation was conducted using MATLAB 2021a on a Windows 10 PC with a quad-core i7 CPU with 16GB RAM with 1000 randomized Monte-carlo simulation samples to evaluate the DOA estimation accuracy. The standard parameters for the study are presented and summarised in Table 1. We selected common parameters in a modern transportation market, as referenced in [10]. It is noteworthy that although we used the EPUMA technique to demonstrate our proposed method in the simulation study, any subspace-based DOA estimation algorithm can be implemented.

TABLE I
Common Simulation Parameters

Parameters	Settings
Carrier Frequency	5500 MHz
Antenna Geometry	Uniformed Linear Array
Array Inter-Element Spacing	$\lambda/2$, where λ is the wavelength of f_c in meters
Simulation Samples	1000
Angle of Interest	30 Degrees
SNR Range	-10 dB to 10 dB

Lastly, we use the RMSE as the primary criterion in our simulation study. In this paper, the general RMSE equation is defined as

$$\mathrm{RMSE} = \sqrt{\frac{1}{Q}\sum_{i=1}^{Q}\left[\frac{\left(\theta_{i_1} - \hat{\theta}_{i_1}\right)^2 + \cdots + \left(\theta_{i_L} - \hat{\theta}_{i_L}\right)^2}{L}\right]} \tag{18}$$

where L is the number of signal sources, Q is the number of simulation data points, θ_i is the actual DOA, and $\hat{\theta}_i$ is the estimated DOA. We also include the Cramer-Rao bound (CRB) [22] as a performance benchmark, where the CRB is computed as

$$\mathrm{CRB} = \frac{\sigma_n^2}{2K}\mathrm{tr}\left(\mathrm{Re}\big((\mathbf{D}^{\mathrm{H}}(\mathbf{I}_M - \mathbf{AA}^{+})\mathbf{D}) \odot \mathbf{R}^{\mathrm{T}}\big)^{-1}\right), \tag{19}$$

with $\mathbf{D} = [\partial\boldsymbol{a}(\theta_1)/\partial\theta_1 \;\; \dots \;\; \partial\boldsymbol{a}(\theta_N)/\partial\theta_N]$ and $\mathbf{R} = \mathrm{E}[\boldsymbol{x}(t)\boldsymbol{x}^H(t)] = \mathbf{AR_sA^H} + \sigma_n^2\mathbf{I}_M$. In this case, $\mathbf{R_s} =$

$\mathbf{E}[\boldsymbol{s}(t)\boldsymbol{x}^{H}(t)]$ is the signal covariance matrix and $\odot$ is the Hadamard matrix product. For root-MUSIC, the FBSS technique improves signal detection and estimation accuracy, where the number of forward-backward subarrays is equal to the number of desired signals.

A. Limited Finite Snapshot Sample Performance with Single Signal Source of Interest

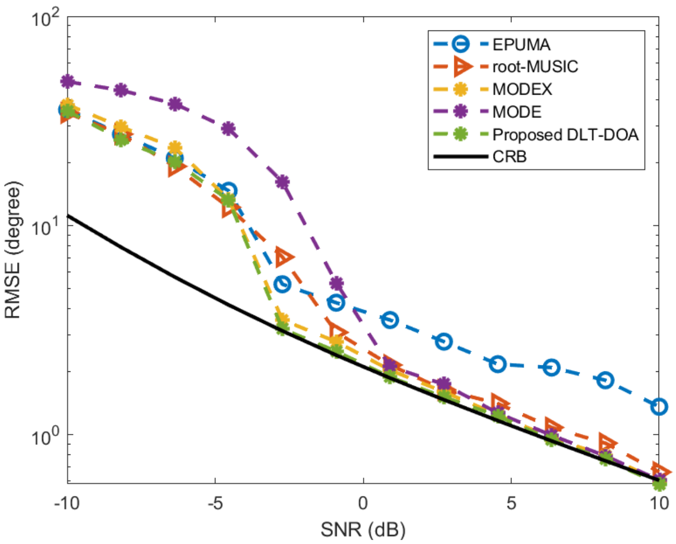

Figure 3: SNR-RMSE Performance for M = 4, N = 1, and K = 10

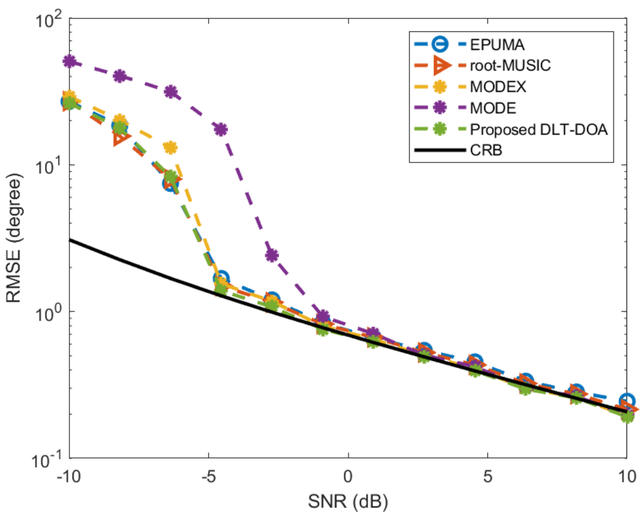

Figure 4: SNR-RMSE Performance for M = 8, N= 1, and K = 10

In this section, we present a scenario where there is a limited, finite number of snapshot samples for a single-source signal of interest.

Fig. 3 and Fig. 4 presents the RMSE of the DOA estimation against varying SNR input received data matrix ranging from -10 to 10 dB where the number of snapshot samples is $K = 10$ and the number of sensor array elements $M = 4$ and $M = 8$, respectively. It is also assumed that the number of impinging signals, $N = 1$ is static and does not deviate with time at the instant of data collection on the receiving end. In addition, Table II presents the RMSE results of all the proposed DOA techniques for comparison.

It is seen in Fig. 3 that our proposed technique outperforms MODE, root-MUSIC, and EPUMA on average when SNR is < -5 dB. Furthermore, the RMSE of our proposed method retains the CRB when SNR is > 3.5 dB. As SNR increases, the RMSE curves of all techniques are tightly bound towards the CRB, and thus, their estimation performance attains the theoretical CRB lower bound curve. The MODE technique does not perform well due to the small number of antenna array elements and a highly limited number of snapshot samples, even though it utilizes the FBSS method to improve DOA estimation. These poor DOA estimation results can be seen generally throughout the entire SNR range. Furthermore, our proposed technique outperforms EPUMA, MODE, and MODEX slightly by 12%. As SNR increases, our proposed method still outperforms the other methods by an average of 7% in terms of DOA estimation performance gain.

Fig. 4 presents a similar simulation environment but with a higher number of antenna array elements. Comparing this with Fig. 3, the performance gained for our proposed method is slightly less when compared to the other techniques. In addition, all DOA estimation techniques presented here approach the CRB limit at a much lower SNR due to the increase in antenna element number. We can observe that MODE performs among the compared techniques at low SNR. Our proposed approach achieves the best DOA estimation performance when the SNR is high at > 3.5 dB. In addition, at high SNR, our proposed technique performs the best when compared to the other demonstrated DOA estimator as it is much closer to the CRB limit.

TABLE II
SUMMARY OF SIMULATION RESULTS FOR SINGLE SIGNAL SOURCE

Scenario	RMSE (Degrees)				
	EPUMA	Root-MUSIC	MODEX	MODE	DLT-DOA
M = 4, SNR = -10 dB	29.9	32.1	36.6	48.5	30.6
M = 4, SNR = 10 dB	1.55	0.66	0.61	0.61	0.60
M = 8, SNR = -10 dB	25.8	24.4	29.8	50.34	26.8
M = 8, SNR = 10 dB	0.23	0.23	0.21	0.66	0.20

B. Limited Finite Snapshot Sample with Multiple Signal Sources of Interest

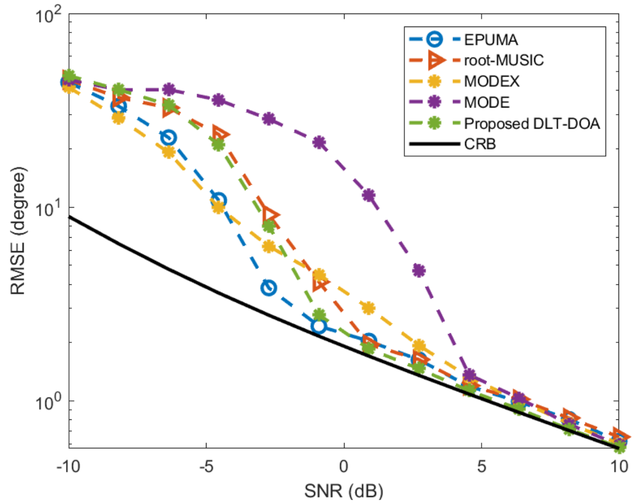

Figure 5: SNR-RMSE Performance for M = 8, N = 2, $\Delta\theta = 10°$, and K = 10

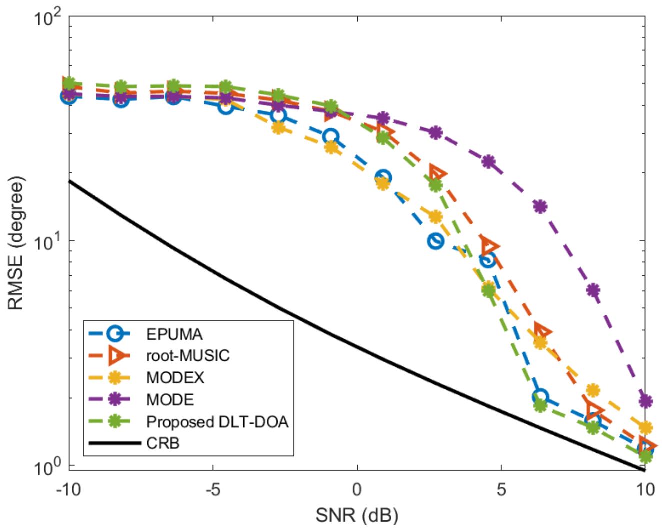

Figure 6: SNR-RMSE Performance for M = 8, N = 2, Δθ=5°, and K = 10

In this example, we conduct a simulation study with a limited number of snapshot samples with two signal sources of interest. Fig. 5 presents a scenario where the signal sources of interest are of an angular separation of 10°. It is clear that the EPUMA technique generally has a better DOA estimation performance – particularly at low SNR of < -5 dB. We want to highlight that the MODE technique has a substantial estimation performance reduction compared to the other techniques. This estimation deficit is because MODE is highly sensitive to the number of signal sources. One potential reason is the symmetric assumption used in the MODE solver algorithm. This reason is consistent across the wide range of scenarios, especially when comparing the results in Fig. 3 and 4. Nevertheless, our proposed technique performs relatively well across the spectrum of SNR. However, EPUMA and root-MUSIC are still outperforming it due to the spatial smoothing modification with an average DOA estimation performance deficit of 7%. At higher SNR of > 0 dB, our proposed method outperforms all the other techniques by 2.8% and is closely bounded by the theoretical CRB limit.

To highlight the DOA estimation resolution among closely spaced signal sources, Fig. 6 presents a scenario where the angular separation is 5°. EPUMA performs best in this scenario in low SNR of < 0 dB and can robustly determine the two closely related signals of interest. Furthermore, root-MUSIC here serves the worse even though it employs the FBSS modification due to the sensitivity in the virtual array setup for spatial smoothing. This result is followed closely by our proposed method in terms of RMSE performance. When SNR is high at > 0 dB, all techniques approach the CRB limit but do not perform as well as in Fig. 5 where the signal sources are separated further. Comparing the DOA estimation performance between Fig. 5 and Fig. 6, our performance difference on average is 15%. In other words, the estimation performance difference results in a 3%/Δθ based on the simulation results. Table III presents a summary of the DOA estimators for multiple signal sources for both the lowest and highest SNR.

TABLE III
SUMMARY OF SIMULATION RESULTS FOR MULTIPLE SIGNAL SOURCES

Scenario	RMSE (Degrees)				
	EPUMA	Root-MUSIC	MODEX	MODE	DLT-DOA
$\Delta\theta = 10°$, SNR = -10 dB	42.1	44.2	38.2	43.6	46.2
$\Delta\theta = 10°$, SNR = 10 dB	0.62	0.64	0.61	0.62	0.59
Δθ=5°, SNR = -10 dB	45.5	48.0	46.7	45.5	50.5
Δθ=5°, SNR = 10 dB	1.17	1.31	1.49	2.14	1.13

C. Single Snapshot Sample with a Single Signal Source of Interest

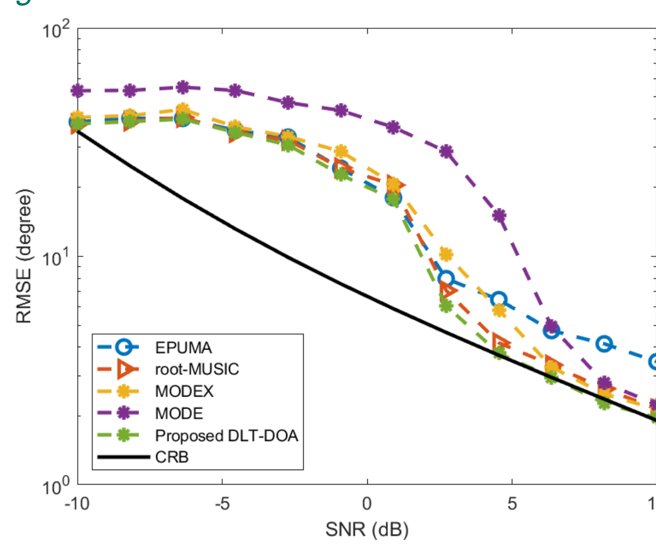

Figure 7: SNR-RMSE Performance for M = 4, N = 1, and K = 1

This section conducts a quantitative analysis of our proposed technique where the number of snapshot samples is $K = 1$. This simulation parameter presents a worst-case scenario where only a single snapshot is available at the array sensor as a limitation where the results are presented in Fig. 7. All other parameters are the same as in the previous section, which can be referred to in Table 1, while Table IV provides the summarized RMSE results of the DOA estimators.

Similarly, the MODE technique performs the worse across the wide range of SNR. Comparing the results in Fig. 6 against a similar simulation environment as in Fig. 3, the DOA estimation only approaches the CRB limit at a much higher SNR. This result is consistent where the number of snapshots changes the raw performance of all the demonstrated DOA estimators. Our proposed technique performs relatively well in a single snapshot scenario compared to EPUMA, root-MUSIC, and MODEX, although the DOA estimation performance difference is negligible at approximately 2%. This phenomenon may be within the margin of error, particularly in low SNR of < 0 dB. We want to highlight the performance difference across the different techniques at high SNR at > 0 dB. Our proposed approach generally performs the best compared to the other methods. This RMSE result is followed closely behind with EPUMA. In general, our proposed method achieves the best estimation performance across the wide range of SNR with an average DOA estimation performance gain of 8.5% compared to the following best estimator.

To that end, the reason why the proposed technique performs better than the rest in a single snapshot environment is mainly due to the optimized diagonal loading factor technique as demonstrated in (13) and the implementation of it in (15). The iterative nature of (13) proves that it is an efficient method in determining accurate DOA estimation as compared to a static diagonal loading factor.

TABLE IV
SUMMARY OF SIMULATION RESULTS FOR SINGLE SNAPSHOT SCENARIO

Scenario	RMSE (Degrees)				
	EPUMA	Root-MUSIC	MODEX	MODE	DLT-DOA
SNR = -10 dB	39.5	40.5	42.4	53.4	41.1
SNR = 10 dB	3.54	2.18	2.05	2.13	1.92

V. CONCLUSION

This paper presents a reconstruction of the sample covariance matrix with uniformed linear arrays in the presence of noise. By effectively utilizing a suitable diagonally loaded value to modify the incoming covariance matrix, we reduce the need for high snapshots in a wide range of SNR environments. Using a modified diagonal loading technique to the sample covariance matrix, our proposed method performs best in a scenario with a minimal number of snapshot samples. This allows the utilization of our algorithm in an environment where the sensors are used small and lightweight without costly hardware for real-world implementation. In addition, high power transmission is not required for accurate DOA estimation for a sensor device emitting a signal due to the excellent performance in low SNR scenarios. It allows fast and precise network directivity and localization in an electronic device like a position sensor for transportation, vehicular systems, or motorsports applications to sense location and orientation in a relatively wide range of SNR and sampling numbers.

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