Enhanced Capon-MUSIC Integration for improved DOA Estimation with Coprime Arrays in Disaster Management

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ABSTRACT

This paper introduces an enhanced Capon beamforming approach that is further integrated with the Multiple Signal Classification (MUSIC) method to achieve superior Direction of Arrival (DOA) estimation using coprime arrays. The proposed enhancement to the standard Capon beamformer focuses on improving its robustness against steering vector mismatches, which significantly boosts its performance in complex signal environments. By optimizing the beamformer's spatial filtering capability, the improved method mitigates signal distortion and enhances resolution. Building on this enhanced Capon beamformer, this study integrates it with the MUSIC method to leverage the strengths of both approaches. The coprime array configuration allows for an increased number of virtual sensors, enabling higher degrees of freedom and improving the resolution of both coherent and uncorrelated signals. This combined Capon-MUSIC framework provides an efficient solution for accurate DOA estimation, even in scenarios where traditional methods fail. The effectiveness of this hybrid approach is evaluated in disaster management applications, where precise signal localization is crucial for tasks such as emergency communication, search and rescue operations, and resource deployment. The simulation results demonstrate that the integrated method outperforms conventional techniques, delivering improved accuracy, robustness, and computational efficiency, making it ideal for real-world disaster response scenarios.

Keywords-enhanced Capon beamforming; MUSIC method; coprime arrays; DOA estimation; disaster management

I. INTRODUCTION

DOA estimation in wireless communications has emerged as a key technique in many applications, such as radar, sensor networks, and wireless communications. Given the increasing complexity of the current sensor arrays and the variety of conditions in which they operate, the need for precise and effective DOA estimation algorithms is greater than ever. Recently, efforts have been made to improve the robustness, accuracy, and efficiency of DOA estimation approaches, especially in complicated scenarios with coherent and uncorrelated sources. For 3D sparse array DOA estimation, the Unitary Root-MUSIC technique with Nyström approximation has been presented as a powerful tool that shows notable gains in estimation accuracy while maintaining computational efficiency [1]. This method is particularly effective in scenarios where traditional approaches struggle, such as dealing with high-dimensional data in sensor networks. Building on this foundation, the Modified Root-MUSIC algorithm was developed to further optimize target localization, allowing for enhanced performance in various applications [2]. In addition, the Adaptive Nyström Spectral Analysis (ANSA) approach has emerged as a viable method for advanced DOA estimation in coprime arrays [3]. This technique enhances the overall estimation quality while addressing the issues associated with constrained sensor combinations. With a focus on coprime sensor arrays, the ECA-MURE algorithm presents a new perspective on high-precision DOA estimation by employing Cramér-Rao Bound (CRB) analysis as a theoretical performance benchmark [4]. In addition, the Manifold Reconstruction Unitary ESPRIT (MR-UESPRIT) algorithm was introduced to optimize the sensor array DOA estimation by utilizing manifold learning approaches [5].

Recent studies have also emphasized the importance of processing speed in DOA estimation. Enhanced processing methods have been developed that allow rapid direction estimation in sensor arrays, thereby improving the system's overall responsiveness [6]. The usefulness of the DOA estimation methods has been further increased by the invention of effective direction estimation algorithms without prior information on the source count for both coherent and uncorrelated sources [7]. The planar-like sensor array design has demonstrated potential for achieving effective DOA estimation, underscoring the possibility of creative array combinations to improve performance [8].

Meanwhile, fast adaptive beamforming techniques have been proposed to optimize the DOA estimation processes, thus improving the overall efficiency of the sensor networks [9]. Moreover, recent advancements in spatially spread acoustic vector sensors have demonstrated improved localization capabilities for near-field sources, further contributing to the growing body of research in DOA estimation [10, 11]. Notably, the trade-off between computational complexity and estimation accuracy continues to be a critical research topic. Practical applications of these theoretical advances have been highlighted by studies focusing on coherent DOA estimation utilizing digital signal processors [12].

The growing interest in machine learning approaches, such as radar signal support vector clustering and feature extraction techniques, reflects the ongoing evolution of DOA estimation methods [13]. As communication technologies continue to advance, the performance analysis of OFDM and OFDM-MIMO systems under fading channels further illustrates the challenges faced in dynamic environments [14]. The design and performance analysis of massive MIMO systems is also gaining traction as researchers aim to increase the capacity of the next-generation networks [15]. The field of DOA estimation is rapidly evolving, driven by the need for innovative algorithms and advanced sensor technologies. This ongoing research not only addresses the current challenges, but also lays the foundation for future developments in adaptive array signal processing and smart antenna design [16, 17].

II. SIGNAL MODEL USING COPRIME SENSOR ARRAYS FOR DOA ESTIMATION

A. Array Observation Model

Let us consider a coprime array consisting of two subarrays, each with M and N sensors (where M and N are coprime integers).

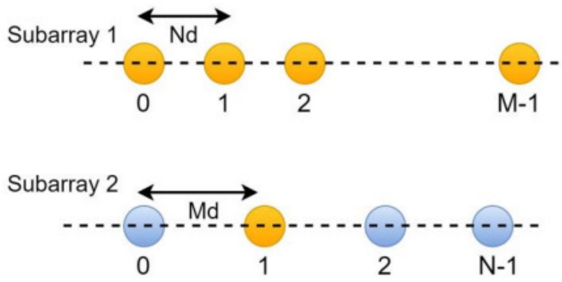

Fig. 1. Illustration of coprime sensor array structure.

The array observation vector $\mathbf{x}(k)$ at time k can be modeled as:

$$\mathbf{x}(k) = \mathbf{A}(\theta)\mathbf{s}(k) + \mathbf{i}(k) + \mathbf{n}(k) \quad (1)$$

where the steering matrix $\mathbf{A}(\theta)$ corresponds to the intended signal entering the moving coprime array from direction θ, $\mathbf{s}(k)$ is the desired signal component vector, $\mathbf{i}(k)$ is the interference component vector, and $\mathbf{n}(k)$ is the noise component vector. The coprime array's steering matrix $\mathbf{A}(\theta)$ can be constructed in the manner described by [18]:

$$\mathbf{A}(\theta) = \begin{bmatrix} \mathbf{a}_M(\theta) \\ \mathbf{a}_N(\theta) \end{bmatrix} \quad (2)$$

where $\mathbf{a}_M(\theta)$ and $\mathbf{a}_N(\theta)$ denote the M-element and N-element steering vectors, respectively.

The array covariance matrix $\mathbf{R}$ can be written as:

$$\mathbf{R} = E\{\mathbf{x}(k)\,\mathbf{x}(k)^H\} = \mathbf{R}_s + \mathbf{R}_{i+n} \quad (3)$$

where E{} is the statistical expectation operator and $(\cdot)^H$ stands for the Hermitian transposition. The signal covariance matrix is $\mathbf{R}_s = E\{\mathbf{s}(k)\,\mathbf{s}(k)^H\} = \sigma_s^2\mathbf{A}(\theta)\mathbf{A}(\theta)^H$ and $\mathbf{R}_{i+n}$ is the representation of the interference-plus-noise covariance matrix. With respect to the array beamformer's weight vector:

$$\mathbf{w} = [w_1, w_2, \cdots, w_{M+N}]^T \quad (4)$$

where the transpose operator is denoted by $[\cdot]^T$, the Signal-to-Interference-Plus-Noise Ratio (SINR) of an output is defined by:

$$\text{SINR} = \frac{\sigma_s^2 \left| \mathbf{w}^H \mathbf{A}(\theta) \right|^2}{\mathbf{w}^H \mathbf{R}_{i+n} \mathbf{w}} \tag{5}$$

In order to maximize the SINR, the focus is on solving an optimization problem. The desired signal power is a critical component in achieving an optimal beamformer.

$$\min_{\mathbf{w}} \ \mathbf{w}^H \mathbf{R}_{i+n} \mathbf{w} \quad \text{s.t.} \quad \mathbf{w}^H \mathbf{A}(\theta) = 1 \tag{6}$$

with the solution provided by [18] as:

$$\mathbf{w}_{opt} = \frac{\mathbf{R}_{i+n}^{-1} \mathbf{A}(\theta)}{\mathbf{A}(\theta)^H \mathbf{R}_{i+n}^{-1} \mathbf{A}(\theta)} \tag{7}$$

In ideal circumstances, it is known that $\mathbf{R}$ can be used instead of $\mathbf{R}_{i+n}$ to simplify the optimization issue in (6) to:

$$\min_{\mathbf{w}} \ \mathbf{w}^H \mathbf{R} \mathbf{w} \quad \text{s.t.} \quad \mathbf{w}^H \mathbf{A}(\theta) = 1 \tag{8}$$

Apparently, in real-world situations, one can only obtain an estimate of the array covariance matrix, which may be obtained from the example data using:

$$\tilde{\mathbf{R}} = \frac{1}{K} \sum_{k=1}^{K} \mathbf{x}(k)\, \mathbf{x}^H(k) \tag{9}$$

where the sample size is denoted by K. Consequently, the typical Capon beamformer is:

$$\mathbf{w}_{Capon} = \frac{\tilde{\mathbf{R}}^{-1} \mathbf{A}(\theta)}{\mathbf{A}(\theta)^H \tilde{\mathbf{R}}^{-1} \mathbf{A}(\theta)} \tag{10}$$

For a given beamformer weight vector **w**, the array output power may be written as:

$$\begin{aligned} P_{output} &= \mathbf{w}^H \mathbf{R} \mathbf{w} = \mathbf{w}^H \mathbf{R}_s \mathbf{w} + \mathbf{w}^H \mathbf{R}_{i+n} \mathbf{w} \\ &= \sigma_s^2 \left| \mathbf{w}^H \mathbf{A}(\theta) \right|^2 + \mathbf{w}^H \mathbf{R}_{i+n} \mathbf{w} \end{aligned} \tag{11}$$

If (8) is used to derive the beamformer, we get:

$$\mathbf{w} = \frac{\mathbf{R}^{-1} \mathbf{A}(\theta)}{\mathbf{A}(\theta)^H \mathbf{R}^{-1} \mathbf{A}(\theta)} \tag{12}$$

and thus:

$$\begin{aligned} P_{output} &= \frac{1}{\mathbf{A}(\theta)^H \mathbf{R}^{-1} \mathbf{A}(\theta)} \\ &= \sigma_s^2 + \frac{\mathbf{A}(\theta)^H \mathbf{R}^{-1} \mathbf{R}_{i+n} \mathbf{R}^{-1} \mathbf{A}(\theta)}{\left| \mathbf{A}(\theta)^H \mathbf{R}^{-1} \mathbf{A}(\theta) \right|^2} \end{aligned} \tag{13}$$

The steering vector can be modeled as follows: In real-world scenarios, errors in the angle estimation of the target signal and errors in the array calibration can result in known steering vector uncertainties. Consequently, it can be used as an estimate of the power of the intended signal since the output power P_{output} is minimized, which also means that the second component on the right-hand side is minimized.

$$\left\| \mathbf{A}(\theta) - \tilde{\mathbf{A}}(\theta) \right\|^2 \le \varepsilon \tag{14}$$

where $\| \cdot \|^2$ denotes the ℓ_2-norm, ε is a known user-defined parameter, and $\tilde{\mathbf{A}}(\theta)$ signifies the nominal steering vector. By resolving the following optimization problem, the steering vector can be estimated according to the principle of the robust Capon algorithm [18]:

$$\min_{\mathbf{A}(\theta)} \ \mathbf{A}(\theta)^H \tilde{\mathbf{R}}^{-1} \mathbf{A}(\theta) \quad \text{s.t.} \quad \left\| \mathbf{A}(\theta) - \tilde{\mathbf{A}}(\theta) \right\|^2 \le \varepsilon \tag{15}$$

This problem is obviously a Second-Order Cone Programming (SOCP) problem, and it can be addressed using the Newton iteration method as described in [7] or by utilizing the tools available in the CVX toolbox [5]. After deriving $\tilde{\mathbf{A}}(\theta)$ as the solution to (15), the power corresponding to the intended signal can be estimated as [18]:

$$\tilde{\sigma}_s^2 = \frac{1}{\tilde{\mathbf{A}}(\theta)^H \tilde{\mathbf{R}}^{-1} \tilde{\mathbf{A}}(\theta)} \tag{16}$$

As a result, the signal covariance matrix estimation can be written as:

$$\tilde{\mathbf{R}}_s = \tilde{\sigma}_s^2 \tilde{\mathbf{A}}(\theta) \tilde{\mathbf{A}}(\theta)^H \tag{17}$$

As previously stated, performance may suffer if the desired signal is present in the training snapshots. In order to improve robustness, the following Improved Noise-Plus-Interference Covariance Matrix (INCM) estimate is used in this proposed method:

$$\tilde{\mathbf{R}}_{i+n} = \tilde{\mathbf{R}} - \tilde{\mathbf{R}}_s = \tilde{\mathbf{R}} - \tilde{\sigma}_s^2 \tilde{\mathbf{A}}(\theta) \tilde{\mathbf{A}}^H \tag{18}$$

It is important to understand that although the INCM can be calculated in the manner outlined, its effectiveness depends on how accurate this estimate is. In order to tackle this, let us designate Δ as the difference between the estimated and actual INCM. This brings us to:

$$\mathbf{R}_{i+n} = \tilde{\mathbf{R}}_{i+n} + \Delta \tag{19}$$

Furthermore, it is presumed that the uncertainty is limited to a particular constraint, which can be stated as:

$$\left\| \Delta \right\|_F \le \gamma \tag{20}$$

The Frobenius norm, denoted as $\| \cdot \|_F$, along with a user-defined positive constant γ, bounds the uncertainty as stated. This sets the stage for an upgraded iteration of the RCapon-INCM beamformer via a worst-case performance optimization strategy as in [18]:

$$\begin{aligned} &\min_{\mathbf{w}} \max_{\Delta} \ \mathbf{w}^H \left(\tilde{\mathbf{R}}_{i+n} + \Delta \right) \mathbf{w} \\ &\qquad \text{s.t.} \ \left\| \Delta \right\|_F \le \gamma, \ \mathbf{w}^H \tilde{\mathbf{A}}(\theta) = 1 \end{aligned} \tag{21}$$

This method is similar to the resilient beamforming described in [2] using a general-rank model. To solve this problem, the Δ maximization problem is first solved as [18]:

$$\max_{\Delta} \quad \mathbf{w}^H\left(\tilde{\mathbf{R}}_{i+n}+\Delta\right)\mathbf{w} \quad \text{s.t.} \quad \|\Delta\|_F \le \gamma \tag{22}$$

The solution to this maximization problem is provided in [2].

$$\Delta = \gamma \frac{\mathbf{w}\mathbf{w}^H}{\|\mathbf{w}\|^2} \tag{23}$$

By rearranging (23) into (21), the following new formulation for the min-max problem is obtained:

$$\min_{\mathbf{w}} \quad \mathbf{w}^H\left(\tilde{\mathbf{R}}_{i+n}+\gamma\mathbf{I}\right)\mathbf{w} \quad \text{s.t.} \quad \mathbf{w}^H\tilde{\mathbf{A}}(\theta)=1 \tag{24}$$

Equation (24) is the reformulated problem with the same structure as (8), where $\mathbf{I}$ is the identity matrix. By using the Lagrange multiplier technique, (24) can be solved as:

$$\mathbf{w}_{RCapon-INCM} = \left[\frac{\left(\tilde{\mathbf{R}}_{i+n}+\gamma\mathbf{I}\right)^{-1}\tilde{\mathbf{A}}(\theta)}{\tilde{\mathbf{A}}(\theta)^H\left(\tilde{\mathbf{R}}_{i+n}+\gamma\mathbf{I}\right)^{-1}\tilde{\mathbf{A}}(\theta)}\right] \tag{25}$$

Therefore, this method yields the RCapon beamformer with INCM estimation, which is now referred to as the RCapon-INCM beamformer. It is also important to note that although the suggested approach considers only one desired signal, it is easily adaptable to situations where there are several desired signals. This extension entails estimating the steering vector and power for every desired signal separately.

III. PROPOSED IMPROVED MUSIC METHOD AND OPTIMIZED SOURCE LOCALIZATION IN DISASTER MANAGEMENT

A popular technique for estimating DOA is the MUSIC algorithm, which takes advantage of the covariance matrix's eigenstructure when processing received signals. The goal in this section is to achieve higher resolution and accuracy in DOA estimation by presenting an improved version of the MUSIC algorithm specifically designed for coprime sensor arrays. Let K uncorrelated narrowband sources that arrive at a coprime sensor array in the directions $\theta=[\theta_1,\theta_2,\ldots,\theta_K]^T$. $|S|=2M+N-1$ sensors form the array, where M and N are coprime integers. Every sensor spacing d is equal to λ/2, where λ is the signal wavelength. At time t over T snapshots, the received signal vector is:

$$\mathbf{x}(t)=\sum_{K=1}^{K}\mathbf{a}_k\mathbf{s}_K(t)+\mathbf{n}(t) \tag{26}$$

$$\mathbf{R}_S = E\left[x(t)x^H(t)\right]=\sum_{K=1}^{K}p_k\mathbf{a}_k\mathbf{a}_K^H+\sigma_n^2\mathbf{I} \tag{27}$$

A. Proposed Algorithm

- Augmented array covariance matrix construction: Define an augmented array covariance matrix $\mathbf{R}_{aug}$ by combining the covariance matrices from two coprime subarrays:

$$\mathbf{R}_{aug}=\begin{bmatrix}\mathbf{R}_{sub1} & 0\\ 0 & \mathbf{R}_{sub2}\end{bmatrix} \tag{28}$$

  where $\mathbf{R}_{sub1}$ and $\mathbf{R}_{sub2}$ are the covariance matrices of the two coprime subarrays.
- Eigenvalue decomposition: Perform eigenvalue decomposition on $\mathbf{R}_{aug}$ to obtain its eigenvalues λ_i and corresponding eigenvectors $\mathbf{e}_i$.
- Compute the MUSIC spectrum: Calculate the MUSIC spectrum $\mathbf{P}_{MUSIC}(\theta)$ for direction θ:

$$\mathbf{P}_{MUSIC}(\theta)=\frac{1}{\mathbf{e}_i^H\mathbf{V}_N\mathbf{e}_i} \tag{29}$$

  where $\mathbf{V}_N$ is the noise subspace spanned by the eigenvectors corresponding to the N smallest eigenvalues of $\mathbf{R}_{aug}$.
- DOA estimation: The peaks in $\mathbf{P}_{MUSIC}(\theta)$ for the estimation of the directions of arrival $\hat{\theta}=[\hat{\theta}_1,\hat{\theta}_2,\ldots,\hat{\theta}_K]^T$.

In the context of disaster management, this study proposes the integration of the enhanced Capon and improved MUSIC algorithms for DOA estimation utilizing coprime arrays. By utilizing these sophisticated algorithms, this method seeks to improve source localization accuracy and efficiency in emergency situations. The suggested approach performs well in challenging environments, enabling a rapid identification of the distress signals and efficient response times in emergency situations.

IV. RESULTS AND DISCUSSION

The parameters used to simulate the proposed method, which integrates the modified Capon beamformer with the MUSIC algorithm, are antenna sensors N=5, M=4, separated by d=0.45λ, and K=400 snapshots. Let us consider the scenario shown in Table I.

TABLE I. INPUT DATA OF INDUCED SIGNALS

Signal no.	DOA	SNR (dB)	K	d
1	-20°	20	400	0.45λ
2	-10°	20	400	0.45λ
3	10°	20	400	0.45λ
4	20°	20	400	0.45λ

Figure 2 displays the simulated spectrum from the proposed method, demonstrating the improved DOA estimation accuracy achieved by integrating the modified Capon beamformer with the MUSIC algorithm. In disaster management, an accurate localization of the signal sources is critical for effective rescue operations. The distinct spectrum peaks indicate four coherent and uncorrelated sources, enabling Unmanned Aerial Vehicles (UAVs) to precisely identify signals from emergency beacons or trapped individuals. This precision enhances the ability to direct rescue teams and deliver aid, significantly improving disaster response capabilities and overall situational awareness in the affected areas.

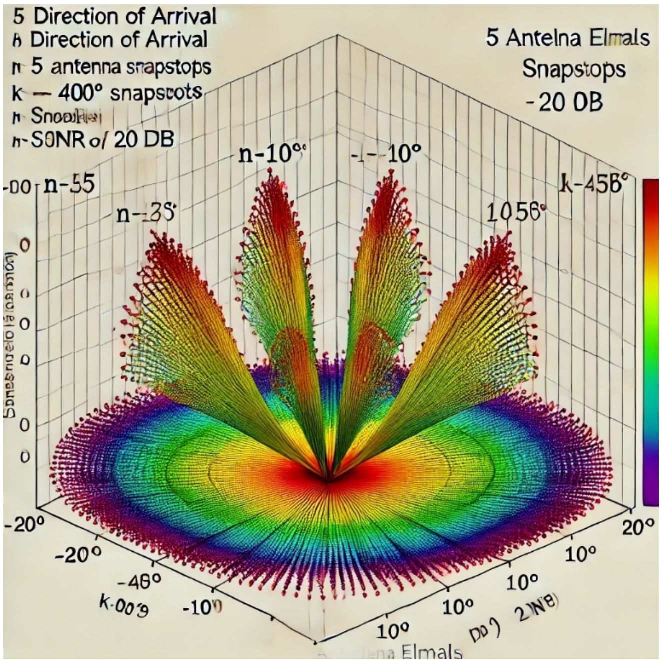

Fig. 2. Pseudo spectrum of proposed algorithm.

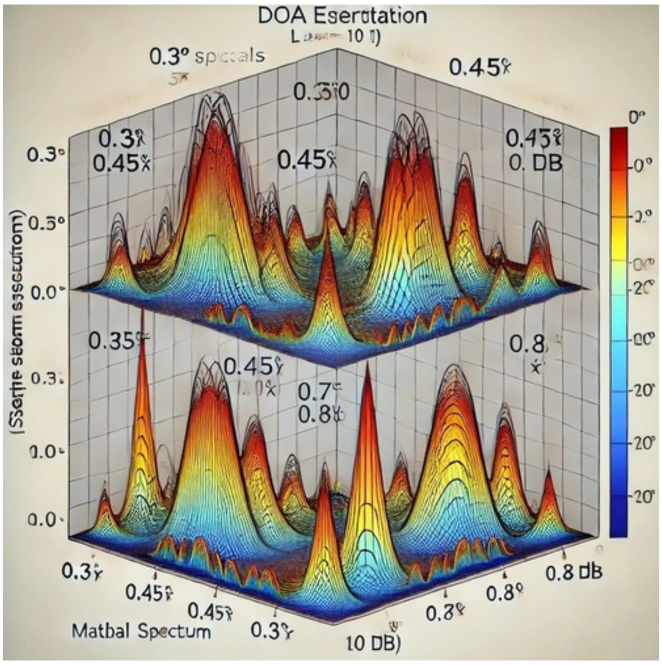

Fig. 3. Spectrum of the Capon beamformer integrated with the modified MUSIC algorithm for effective signal localization in disaster management (N=5 and M=6, with d=0.3λ, 0.45λ, 0.7λ, 0.8λ, and λ).

The performance of the proposed method was also evaluated with different inter-element spacings in a smart antenna system. Figure 3 depicts the simulated spectrum of the proposed approach. It shows the performance of DOA estimation under varying inter-element spacings (d=0.3λ, 0.45λ, 0.7λ, 0.8λ, and λ) for two narrowband signals with DOAs 0° and 40°, SNR 20 dB, and antenna sensors N=5, M=4. The graph illustrates how inter-element spacing affects DOA clarity in the proposed approach, with excessive spacing resulting in unwanted lobes that can complicate signal localization in practical disaster management or other applications requiring precise direction finding. The key observations are:

- Grating lobes: At larger spacings, specifically d=0.7λ, 0.8λ, and λ, multiple major peaks, known as grating lobes, appear in the spectrum. This phenomenon introduces ambiguity into the DOA estimation, as the algorithm may misinterpret these additional peaks as potential directions of arrival.
- Performance with smaller spacings: At smaller spacings (e.g., d=0.3λ and 0.45λ), the spectrum exhibits clear peaks at the actual DOAs (0° and 40°) without significant grating lobes, ensuring more accurate DOA estimation.
- Optimal DOA estimation: A good DOA estimation is obtained when the inter-element spacing is between d=0.45λ and 0.55λ. This range improves signal localization accuracy and reduces grating lobes.
- Effect of large inter-element spacing: The system generates more lobes than necessary when the inter-element spacing exceeds 0.6λ, which can result in inaccurate signal localization.

These results suggest that with careful selection of inter-element spacing, the proposed method can achieve accurate and reliable DOA estimation for disaster management applications. Even in complex environments, UAVs with sophisticated antenna systems can find signals from emergency beacons or trapped people by optimizing the spacing. The integration of the Capon beamformer with the updated MUSIC algorithm ensures accuracy and robustness, making it a useful tool for disaster response and management. Accurate signal localization facilitates quick and efficient rescue efforts, increasing the likelihood of saving lives in dire circumstances.

The Root Mean Square Error (RMSE) versus the Signal-to-Noise Ratio (SNR) analysis is an essential tool for assessing the effectiveness of different DOA estimation techniques in the context of disaster management. In this study, the proposed approach is compared with well-known methods, such as ESPRIT, UR-MUSIC, ECS-MUSIC, and MUSIC. Four uncorrelated narrowband sources and two coherent signals with a 0.5λ spacing were considered. The signals arrived from angles of 10°, 15°, 20°, 25°, and -5°. During the simulations, 100 snapshots were taken at 10 dB SNR. The results, portrayed in Figure 4, demonstrate how well the proposed strategy minimizes RMSE compared to the alternative approaches.

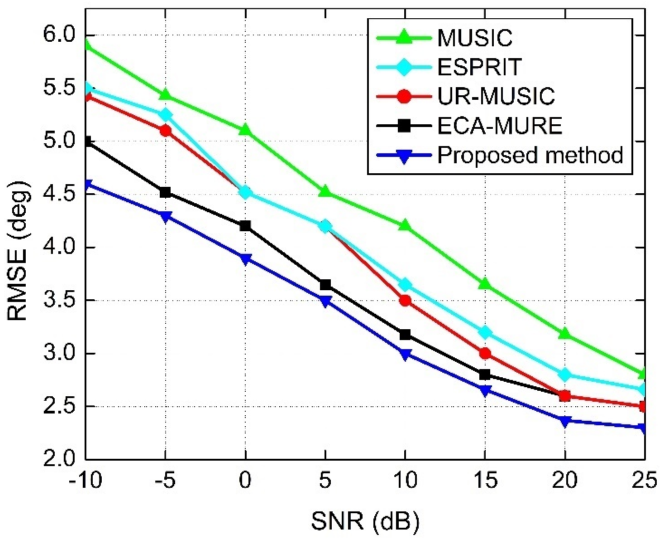

Fig. 4. RMSE versus SNR for various methods.

The order of accuracy found was MUSIC, ESPRIT, UR-MUSIC [2], ECA-MUSIC [4], and finally the proposed method. This suggests that the current sudy's combination of the modified Capon beamformer with the MUSIC algorithm results in better localization performance in noisy environments. This improved accuracy is important for disaster management scenarios, where accurate localization of signals, such as emergency beacons or communications from trapped individuals, is necessary for prompt and successful rescue operations. Accurately determining the direction of multiple signal sources improves situational awareness and enables more effective resource deployment in disaster areas. As a result, the proposed method contributes significantly to improving the reliability and effectiveness of disaster response operations.

V. CONCLUSION

This study presented a method integrating the modified Capon beamformer with the Multiple Signal Classification (MUSIC) algorithm to improve Direction of Arrival (DOA) estimation for disaster management applications. The simulations revealed that the optimal inter-element spacing, specifically between 0.45λ and 0.55λ, significantly improves localization accuracy by minimizing the grating lobes. The proposed method demonstrated superior performance in reducing the Root Mean Square Error (RMSE) when compared to established techniques, such as MUSIC, ESPRIT, UR-MUSIC, and ECA-MUSIC. The results highlight the critical importance of accurate signal detection in disaster scenarios, as a precise localization of emergency signals is essential for efficient rescue operations. Overall, this integration provides a robust solution that enhances situational awareness and improves the effectiveness of disaster response efforts, ultimately contributing to better outcomes in life-saving situations.

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