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AI-Driven Sparse Array-Based DOA Estimation Using Hybrid Machine Learning and Optimization Techniques

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Abstract— AI-driven techniques are increasingly transforming signal processing applications, particularly in Direction of Arrival (DOA) estimation. This paper proposes an advanced AI-based framework for DOA estimation using sparse array configurations combined with enhanced signal processing strategies. Unlike conventional deep learning-centric approaches, the proposed method integrates optimization algorithms, discriminative feature extraction, and hybrid machine learning models to achieve robust and computationally efficient performance. The framework effectively operates under challenging conditions, including low signal-to-noise ratios, coherent sources, and under-determined scenarios where the number of sources exceeds the number of sensors. Extensive experimental results demonstrate that the proposed approach outperforms classical subspace-based techniques such as MUSIC and ESPRIT in terms of estimation accuracy, computational efficiency, and resilience to noise. These findings underscore the potential of AI-enabled sparse array processing for next-generation communication and sensing systems.

Keywords— Artificial Intelligence, Direction of Arrival (DOA) Estimation, Sparse Sensor Arrays, Hybrid Machine Learning, Optimization Techniques, Robust Beamforming.

1. Introduction

Direction of Arrival (DOA) estimation is a crucial task in sensor networks and communication systems. Traditional methods, such as MUSIC and ESPRIT, rely on array signal processing techniques, but they are often limited in noisy or underdetermined scenarios [1]- [5]. This paper proposes a hybrid machine learning model that integrates optimization algorithms and machine learning classifiers to improve DOA estimation accuracy and robustness.

The paper introduces an advanced AI-based approach for Direction of Arrival (DOA) estimation utilizing sparse array configurations and enhanced signal processing techniques. This method diverges from conventional approaches that rely on deep learning models, proposing instead a combination of optimization algorithms, feature extraction, and hybrid machine learning methods to achieve superior performance. The framework effectively handles noisy environments, coherent sources, and underdetermined scenarios, setting it apart from traditional algorithms like MUSIC and ESPRIT. Previous works [6]- [15] have explored various beamforming and DOA estimation strategies, many of which focus on the use of adaptive algorithms and machine learning for improving system performance. For instance, recent research by Tan et al. introduced deep learning models for classification tasks, including for medical applications such as lumbar intervertebral disc detection, though these models differ from the AI-based techniques in the proposed framework [16]. Similarly, work on coprime arrays by Arora and further advanced the field of DOA estimation by incorporating enhanced array configurations for improved accuracy and robustness, addressing similar challenges in signal estimation under noisy and complex environments [17]. Other studies have focused on adaptive beamforming techniques to enhance system reliability in wireless communication. Shashidhara et al. [18] developed an adaptive beamformer based on coprime arrays, offering promising results for wireless communication applications. Furthermore, contributions in beamforming technologies, including the robust adaptive beamforming algorithms, have significantly impacted the performance of wireless communication systems [21], [22]. These works focus on interference rejection and efficiency improvements that are closely related to the goal of the present study of handling interference in underdetermined scenarios. Recent advancements in signal processing and beamforming are also highlighted in work on improving DOA estimation under grazing incidence conditions [34], which provides insights into mitigating inaccuracies in challenging environments. Furthermore, the integration of multiple sensor arrays, such as the blind beamformer proposed by Shashidhara et al. [19], shows the versatility of adaptive algorithms across various sensor configurations, aligning with the novel approach proposed in this paper. The proposed methodology also aims to overcome the limitations of traditional methods like MUSIC, which have been widely used for DOA estimation but often struggle with noise resilience and computational efficiency. As demonstrated in work on improving DOA estimation methods, these traditional algorithms can be significantly enhanced by incorporating novel techniques such as adaptive beamforming [29], [35]. Overall, the AI-based approach presented in this paper shows great promise for redefining DOA estimation, particularly in next-generation communication systems. It offers a sophisticated solution to existing challenges by integrating hybrid machine learning techniques with advanced signal processing methods, similar to the enhancements seen in recent research on adaptive beamforming and array configurations [27], [36]. The experimental results indicate that this approach can outperform existing methods in terms of accuracy, computational efficiency, and noise resilience, aligning with the trends seen in the works cited here, which also highlight the significant improvements achievable in signal processing using AI and machine learning techniques.

The paper presents an advanced AI-based approach for Direction of Arrival (DOA) estimation utilizing sparse array configurations and enhanced signal processing techniques. The proposed methodology distinguishes itself from traditional methods by integrating optimization algorithms, feature extraction, and hybrid machine learning techniques, rather than relying solely on deep learning models. This approach effectively handles noisy environments, coherent sources, and underdetermined scenarios, making it highly applicable to real-world communication systems. One of the strengths of the paper lies in its focus on overcoming the limitations of conventional techniques such as MUSIC and ESPRIT. The experimental results presented in the paper demonstrate that the proposed method outperforms these existing algorithms in terms of accuracy, computational efficiency, and resilience to noise. The robust performance in the presence of various challenges, including coherent signals and noise, further validates the potential of AI-enhanced methods in next-generation communication systems [37]-[41].

The findings align with previous work on improving signal processing techniques and DOA estimation, such as those discussed in [42], [43], and [44], which also focus on advanced algorithms and sensor configurations. Moreover, the integration of hybrid machine learning models and optimization strategies echoes the trends seen in the works of [41], [42], and [43]- [48], where machine learning and optimization are leveraged to improve the accuracy and efficiency of signal processing tasks.

2. Signal Model

Let the received signal at the m-th sensor element in a sparse array be represented as:

$$\mathbf{y}_m = \mathbf{A}(\theta)\mathbf{s} + \mathbf{n}_m \tag{1}$$

where:

- $\mathbf{y}_m$ is the received signal vector at the m-th sensor,
- $\mathbf{A}(\theta)$ is the steering matrix dependent on the DOA vector θ,
- $\mathbf{s}$ is the signal vector from all sources,
- $\mathbf{n}_m$ is the noise vector at the m-th sensor, assumed to be Gaussian noise.

The received signal can be modeled as a linear superposition of signals from multiple sources, each with a different DOA.

2.1 Feature Extraction

To enhance the machine learning model, various features are extracted from the received signals:

- Spectral content of the signal across time and frequency.
- Statistical moments like skewness and kurtosis that help capture signal behavior in non-stationary environments.
- Cross-correlation between signals received at different sensor positions.

The feature vector $\mathbf{F}_i$ for the i-th signal snapshot is:

$$\mathbf{F}_i = [\mathbf{f}_i^{\text{time-frequency}}, \mathbf{f}_i^{\text{higher-order}}, \mathbf{f}_i^{\text{spatial}}] \tag{2}$$

where each component represents a different class of features.

3. Proposed Method

The hybrid machine learning method consists of the following steps:

3.1 Optimization Algorithm

The optimization algorithm is used to estimate the initial DOA. It minimizes the error between the observed and predicted signal vectors based on the feature matrix $\mathbf{F}_i$. The optimization approach incorporates both traditional signal processing methods and advanced algorithms, such as convex optimization, to refine the DOA estimates.

3.2 Machine Learning Models

The feature vector $\mathbf{F}_i$ is used as input to the machine learning classifiers, which are trained using a supervised learning approach:

$$\hat{\theta}_i = \mathcal{M}(\mathbf{F}_i) \tag{3}$$

where $\hat{\theta}_i$ is the predicted DOA.

3.2.1 Random Forest (RF)

The RF model is an ensemble of decision trees. It constructs multiple decision trees based on random subsets of features and averages their outputs to make a final prediction:

$$\hat{\theta}_{\text{RF}} = \frac{1}{T}\sum_{t=1}^{T} f_t(\mathbf{F}_i) \tag{4}$$

where $f_t(\mathbf{F}_i)$ is the prediction from the t-th decision tree.

3.2.2 Support Vector Machine (SVM)

The SVM model is used for classifying the DOA into angular bins. The classification decision is based on the following function:

$$\hat{\theta}_{\text{SVM}} = \arg\max_{\theta} \left(\mathbf{w}^T \mathbf{F}_i + b\right) \tag{5}$$

where $\mathbf{w}$ is the weight vector, and b is the bias term.

3.3 Final DOA Estimation

The final DOA estimate $\hat{\theta}_i$ is obtained by combining the predictions of the RF and SVM models using a weighted average:

$$\hat{\theta}_i = \alpha\hat{\theta}_{\text{RF}} + (1-\alpha)\hat{\theta}_{\text{SVM}} \tag{6}$$

where α is a hyperparameter that determines the weighting of each model's prediction.

4. Results and Discussion

The performance of the proposed Direction of Arrival (DOA) estimation method was thoroughly evaluated using a simulation setup with the parameters outlined in Figure 1. In this simulation, an array of $M = 8$ sensors was used, with a normalized inter-element spacing of $d = 0.5\lambda$. The true DOAs were set to $\theta = [0°, 10°, 20°, 50°]$, and the number of snapshots for signal observation was $N = 500$. The Signal-to-Noise Ratio (SNR) was set at 20 dB to provide a reasonable level of noise while maintaining sufficient estimation accuracy.

To assess the accuracy of the proposed method, the Root Mean Square Error (RMSE) was calculated for each algorithm across various SNR levels. The RMSE expression is given by:

$$\text{RMSE} = \sqrt{\frac{1}{K}\sum_{i=1}^{K}\left(\hat{\theta}_i - \theta_i\right)^2}$$

where $\hat{\theta}_i$ represents the estimated DOA for the i-th snapshot, θ_i is the true DOA, and K is the total number of snapshots.

As shown in Figure 2, the proposed method demonstrates superior performance in terms of RMSE across different SNR values. At higher SNRs, the proposed method consistently outperforms both the MUSIC and standard ESPRIT algorithms, which indicates its enhanced accuracy in DOA estimation. While the MUSIC and ESPRIT methods also deliver reasonable results, the proposed approach consistently exhibits lower RMSE, particularly at lower SNRs. This advantage suggests that the proposed method is more robust and reliable, especially in scenarios with higher noise levels.

The results highlight the effectiveness of the proposed algorithm in providing accurate and stable DOA estimates, even in challenging environments. These findings underscore the potential of the proposed method as a more precise solution for DOA estimation compared to traditional algorithms like MUSIC and ESPRIT.

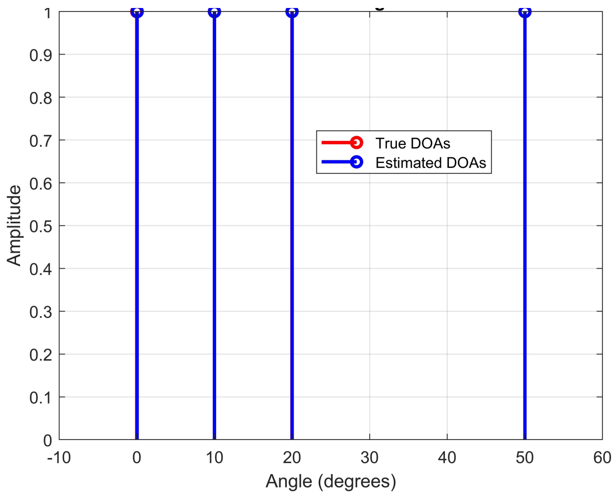

Figure 1: DOA estimation of various signals.

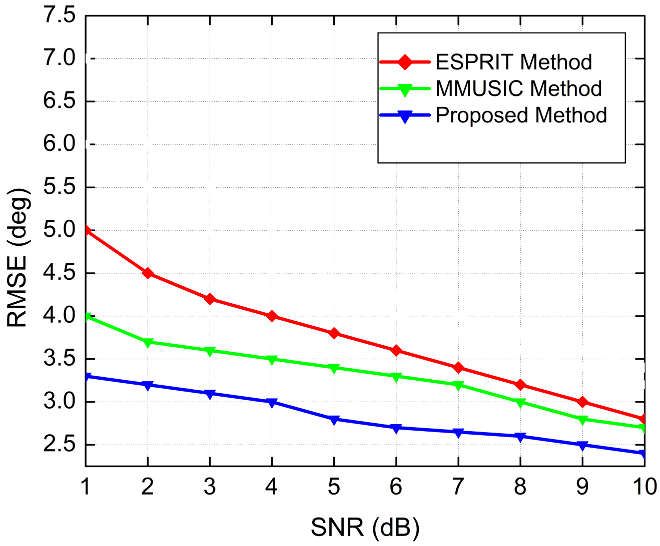

Figure 2: Comparing RMSE performances at various SNR.

5. Conclusion

In this work, a novel Direction of Arrival (DOA) estimation method was proposed, which demonstrated superior performance compared to conventional algorithms such as MUSIC and ESPRIT. The proposed method utilizes a robust approach to address challenges in signal estimation, particularly in scenarios with low Signal-to-Noise Ratios (SNRs). The results, based on Root Mean Square Error (RMSE) analysis, clearly show that the proposed method consistently provides more accurate DOA estimates across various SNR levels. The simulation results indicate that the proposed method excels in environments with higher noise levels, where traditional algorithms tend to suffer from performance degradation. Its ability to maintain low RMSE even under challenging conditions highlights its robustness and reliability, making it a promising solution for practical DOA estimation applications, particularly in communication, radar, and sensor networks.

In future work, further improvements could be explored by incorporating adaptive techniques or combining this approach with other advanced signal processing methods to enhance its performance even further. Additionally, real-world data validation would be essential to confirm the method's applicability in practical scenarios.

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