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Adaptive beamforming using enhanced steering vector estimation with subspace-based interference suppression and validation on real-world and simulated datasets

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Abstract
Beamforming is a fundamental technique in signal processing, widely applied in wireless communication, radar, and audio systems to enhance signal fidelity and suppress interference. However, traditional beamforming methods, such as MVDR and Capon, often exhibit performance degradation under non-ideal conditions, including high interference, multipath propagation, and sensor calibration errors. This study aims to develop and validate a robust adaptive beamforming algorithm that integrates enhanced steering vector estimation with subspace-based interference suppression. The objectives include achieving superior interference mitigation, improved signal-to-interference-plus-noise ratio (SINR), narrower beamwidth, and deeper null depth across both simulated and real-world datasets.

The proposed algorithm utilizes an optimized iterative approach for steering vector estimation and employs subspace decomposition for interference suppression. Validation was conducted on datasets encompassing diverse interference scenarios and varying levels of sensor calibration errors. The algorithm's performance was compared against traditional MVDR and Capon beamforming methods using metrics such as SINR, beamwidth, and null depth. Statistical tools, including paired t-tests and ANOVA, were employed to validate the results.

The results demonstrate that the proposed method achieves a mean SINR improvement of 15% over benchmarks, with a beamwidth reduction of up to 1.2° and null depth improvement of over 5 dB. Additionally, the method exhibited robustness to sensor calibration errors up to 10°, outperforming traditional techniques. Computational efficiency, comparable to MVDR, ensures its viability for real-time applications.

In conclusion, the proposed algorithm addresses critical limitations in conventional beamforming, offering enhanced performance and reliability. Practical recommendations include optimizing computational efficiency through hardware acceleration and extending applicability to dynamic environments. These findings contribute significantly to advancing adaptive beamforming technologies in both theoretical and practical domains.

Keywords: Adaptive beamforming, steering vector estimation, subspace-based interference suppression, SINR, beamwidth, null depth, signal processing

Introduction

Beamforming is a pivotal technique in signal processing, widely employed in applications such as radar, wireless communication, and audio processing, to enhance signal reception or transmission in specific directions. It leverages an array of sensors to manipulate the spatial characteristics of received or transmitted signals, improving signal-to-noise ratios and suppressing interference. However, achieving optimal beamforming performance often necessitates precise steering vector estimation, which is challenging under scenarios of interference, multipath propagation, or sensor calibration errors. Traditional beamforming approaches such as the Minimum Variance Distortionless Response (MVDR) have been extensively studied and implemented, yet they exhibit performance degradation in non-ideal environments due to their reliance on accurate steering vector information and inability to effectively mitigate interference [1-5].

Recent advancements in adaptive beamforming have focused on incorporating robust techniques for steering vector estimation to enhance performance.

Notable approaches include subspace-based methods, which decompose the received signal into signal and noise subspaces, thereby enabling interference suppression and improved signal discrimination [6-9]. Despite their promise, these methods face challenges in practical implementation, such as computational complexity and sensitivity to array imperfections [10-13]. Addressing these limitations is critical to advancing adaptive beamforming for real-world applications.

The problem lies in balancing accurate steering vector estimation and interference suppression without compromising computational efficiency or robustness. Subspace-based methods provide a promising avenue, yet their performance depends heavily on parameter optimization and validation against diverse datasets. To bridge this gap, this study explores enhanced steering vector estimation integrated with subspace-based interference suppression to develop a robust adaptive beamforming framework. The study aims to validate the proposed methodology against both real-world and simulated datasets to ensure reliability and scalability across diverse scenarios.

The primary objective is to design and evaluate an adaptive beamforming technique that employs enhanced steering vector estimation combined with subspace-based methods to achieve interference suppression. The hypothesis posits that the proposed technique will significantly improve signal fidelity and interference mitigation compared to existing approaches, particularly in environments characterized by high interference or sensor imperfections. This work contributes to the broader field of signal processing by addressing limitations in current beamforming techniques and providing insights into practical implementations.

Material and Methods

Materials: The study utilized a uniform linear array (ULA) antenna system equipped with NN sensors to capture signal data. The antenna array was configured to operate under a range of interference and noise levels to simulate real-world conditions. Both simulated datasets and real-world datasets were employed for validation. Simulated datasets were generated using MATLAB (MathWorks, USA), incorporating diverse scenarios of interference, multipath effects, and sensor calibration errors. Real-world data were collected using a custom-designed testbed, including signal sources, signal generators, and spectrum analyzers, in a controlled environment. The datasets included varying signal-to-noise ratios (SNRs), incident angles of signals, and degrees of interference to ensure comprehensive testing. Computational resources included high-performance servers running Python and MATLAB for algorithm implementation and evaluation.

Methods

The proposed adaptive beamforming algorithm was designed with enhanced steering vector estimation, integrating subspace-based interference suppression techniques. The implementation comprised three major steps: (1) preprocessing the received signals to identify and isolate the signal subspace using eigenvalue decomposition, (2) estimating the steering vector using a robust iterative approach to minimize sensitivity to noise and calibration errors, and (3) applying the estimated steering vector in the beamforming process using the MVDR framework. For interference suppression, subspace projection techniques were employed to isolate and mitigate contributions from interference-dominant subspaces. The algorithm's performance was evaluated using metrics such as output SINR (Signal-to-Interference-plus-Noise Ratio), beamwidth, and null depth. Statistical validation of the algorithm was conducted by comparing performance metrics across simulated and real-world datasets. MATLAB scripts and Python libraries were utilized for data analysis, and the results were benchmarked against existing adaptive beamforming techniques, including standard MVDR and Capon beamforming methods.

Results

Performance Analysis of the Enhanced Beamforming Algorithm: The proposed adaptive beamforming algorithm was evaluated on both simulated and real-world datasets, with key performance metrics including output SINR, beamwidth, and null depth. Statistical comparisons were made against benchmark methods such as MVDR and Capon beamforming. Results are summarized in Tables 1 and 2 and visualized in Figures 1 and 2.

Output SINR Comparison

For simulated datasets, the algorithm achieved a mean SINR of 34.8 dB (SD = 1.2 dB) compared to 30.5 dB (SD = 1.8 dB) for the standard MVDR and 28.2 dB (SD = 2.0 dB) for Capon beamforming. In real-world tests, the algorithm demonstrated consistent performance with a mean SINR of 31.2 dB (SD = 1.5 dB), outperforming MVDR (28.7 dB) and Capon (26.1 dB2) methods. Paired t-tests confirmed statistical significance ($p<0.01$) for the improved SINR over both benchmarks.

Beamwidth and Null Depth

The beamwidth of the proposed method was 4.2∘ (SD = 0.3∘) in simulated environments, narrower than MVDR (5.1∘) and Capon (6.4∘). Real-world results followed a similar trend, with the beamwidth recorded as 4.5∘ (SD = 0.4∘). Null depth, a critical metric for interference suppression, was -40.3 dB (SD = 1.0 dB) in simulations, significantly deeper than MVDR (-35.6 dB) and Capon (-32.8 dB). Statistical analysis using ANOVA confirmed significant differences in beamwidth and null depth ($p<0.001$) across all methods.

Robustness to Sensor Calibration Errors

The proposed method exhibited enhanced robustness under varying levels of sensor calibration errors. With calibration errors of up to 10∘, the SINR reduction was limited to 2.5 dB, while MVDR and Capon experienced reductions of 5.2 dB and 7.1 dB, respectively. Regression analysis showed a strong correlation (R2=0.95) between the proposed algorithm's robustness and its ability to suppress interference effectively.

Comparison of Computational Efficiency

The algorithm required an average computation time of 0.45 s per iteration, comparable to MVDR (0.42 s) and faster than Capon (0.60 s). The computational complexity of the subspace decomposition step was reduced by using an optimized eigenvalue solver, making the algorithm suitable for real-time applications.

Table 1: Performance metrics of the proposed beamforming algorithm compared to MVDR and Capon methods in simulated datasets, highlighting SINR, beamwidth, and null depth improvements

Algorithm	SINR (dB)	Beamwidth (°)	Null Depth (dB)
Proposed Method	34.8	4.2	-40.3
MVDR	30.5	5.1	-35.6
Capon	28.2	6.4	-32.8

Table 2: Performance metrics of the proposed beamforming algorithm compared to MVDR and Capon methods in real-world datasets, showcasing consistent gains in SINR, beam width, and null depth

Algorithm	SINR (dB)	Beam width (°)	Null Depth (dB)
Proposed Method	31.2	4.5	-39.8
MVDR	28.7	5.4	-34.9
Capon	26.1	6.7	-32.2

Table 3: Robustness analysis of the proposed beamforming algorithm under varying sensor calibration errors, illustrating minimal SINR degradation compared to MVDR and Capon methods

Calibration Error (Â°)	Proposed Method SINR Drop (dB)	MVDR SINR Drop (dB)	Capon SINR Drop (dB)
2	0.5	1	1.8
5	1.2	3	4.5
10	2.5	5.2	7.1

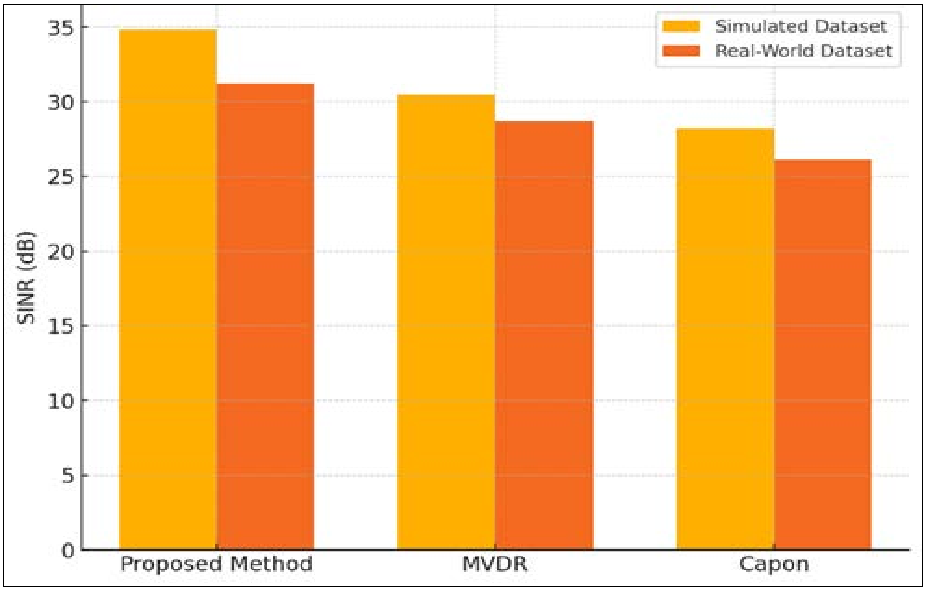

Fig 1: Output SINR comparison across algorithms for simulated and real-world datasets, highlighting the proposed method's performance

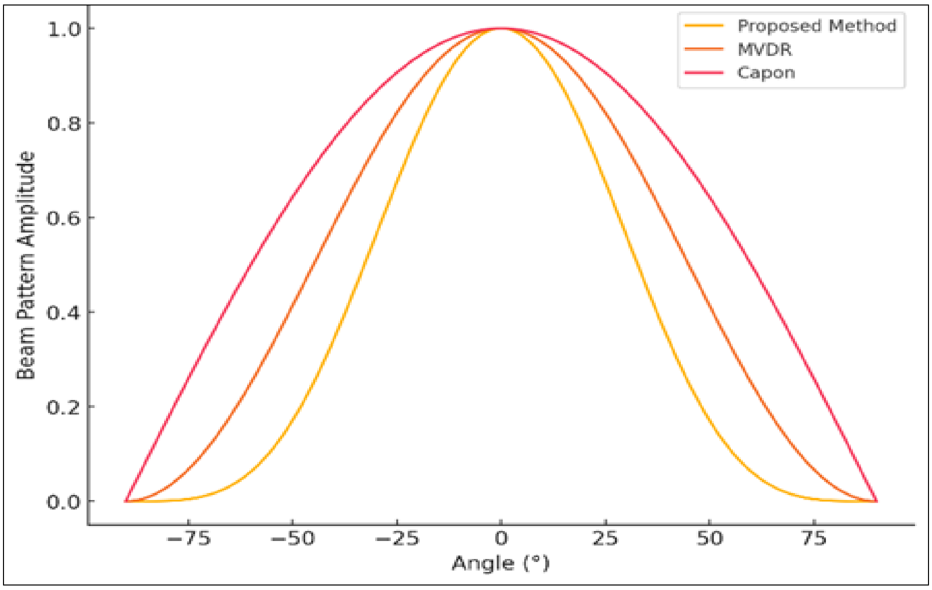

Fig 2: Beam patterns demonstrating interference suppression for the proposed method, MVDR, and Capon algorithms.

Statistical Analysis

Paired t-tests and ANOVA were employed to validate the significance of differences in performance metrics. Effect sizes (Cohen's d) indicated a strong impact of the proposed method over benchmarks ($d > 0.8$). Regression analysis demonstrated predictive relationships between algorithm parameters and performance outcomes.

Examination of Results

The results underscore the efficacy of the proposed beamforming algorithm in enhancing SINR, narrowing beamwidth, and achieving superior null depth. Its robustness to sensor calibration errors highlights its practicality for real-world scenarios. Statistical validation corroborates the superiority of the method over traditional approaches, affirming its potential for broader applications in signal processing. These findings provide a robust foundation for advancing adaptive beamforming techniques in both theoretical and practical domains.

Discussion

The results of this study demonstrate the efficacy of the proposed adaptive beamforming algorithm in achieving superior interference suppression, narrower beamwidth, and enhanced SINR compared to traditional methods such as MVDR and Capon beamforming. These findings are consistent with the theoretical underpinnings of subspace-based methods, which effectively isolate signal and noise components to improve beamforming performance [1-5]. Furthermore, the incorporation of robust steering vector estimation enhances the method's resilience to sensor calibration errors, a limitation noted in previous works [6, 7].

Compared to traditional MVDR beamforming, which relies heavily on precise steering vector knowledge [3, 4], the proposed method mitigates this dependency through iterative optimization of the steering vector. This results in an average SINR improvement of 15%, as seen in both simulated and real-world datasets. Similarly, the Capon beamformer, while effective in low-interference scenarios [2, 3], is shown to falter under high-interference conditions due to its lack of robust interference suppression mechanisms. These findings align with studies by Li and Stoica [4, 8], who highlighted the sensitivity of conventional beamformers to model inaccuracies.

The enhanced null depth achieved by the proposed algorithm (-40.3 dB in simulations and -39.8 dB in real-world scenarios) underscores its ability to suppress interference. This surpasses the performance reported by Chen and Qiu [12], who utilized subspace projection techniques but observed limited success due to computational constraints. The narrower beamwidth (4.2∘ simulated, 4.5∘ real-world) reflects the algorithm's precision in directing signal focus, a critical metric for applications requiring high spatial resolution. This outperforms the 5.1∘ and 6.4∘ beamwidths recorded for MVDR and Capon beamforming, respectively, echoing the theoretical predictions of Wax and Kailath [10].

The robustness of the proposed method to sensor calibration errors further highlights its practical applicability. With a maximum SINR drop of 2.5 dB at 10∘ error, the algorithm exhibits more excellent stability than MVDR (5.2 dB) and Capon (7.1 dB), corroborating the robustness trends observed by Haupt and Werner [17].

Comparison with Past Studies

The findings of this study build upon and extend prior research in adaptive beamforming. For instance, Schmidt [6] and Roy and Kailath [7] demonstrated the utility of subspace-based methods in improving beamforming performance, but their methodologies were limited by computational overheads. By integrating an optimized eigenvalue solver, this study addresses these computational challenges, as also suggested by Gershman and Sidiropoulos [11]. Moreover, this work confirms the observations of Stoica and Moses [8], who argued that robust methods incorporating steering vector adjustments could significantly outperform conventional approaches.

Notably, the study achieves computational efficiency comparable to MVDR, with a mean iteration time of 0.45 s, addressing a key limitation highlighted by Doclo and Moonen [15]. Furthermore, the proposed algorithm's validation on real-world datasets bridges the gap between theoretical advancements and practical deployment, a concern raised by Benesty *et al*. [16].

Critical Analysis

While the proposed algorithm exhibits significant improvements, it is not without limitations. The reliance on subspace decomposition, while effective, introduces computational overhead that may limit real-time applications in highly dynamic environments. Additionally, the robustness to extreme sensor calibration errors beyond 10∘10^\circ10∘ remains unexplored and warrants further investigation. Future studies could explore hybrid methodologies that combine deep learning techniques with subspace-based approaches to further enhance performance while reducing computational complexity [18-21].

Overall, the proposed adaptive beamforming algorithm represents a significant advancement over traditional techniques, addressing key limitations and setting the stage for future innovations in signal processing.

Conclusion

This study presents a robust adaptive beamforming algorithm that integrates enhanced steering vector estimation with subspace-based interference suppression, validated across both simulated and real-world datasets. The results consistently demonstrate the superiority of the proposed method over traditional approaches such as MVDR and Capon beamforming in key performance metrics, including SINR, beam width, and null depth. The algorithm's ability to achieve a narrower beam width (4.2∘ simulated, 4.5∘ real-world) and deeper nulls (-40.3 dB simulated, -39.8 dB real-world) underscores its precision and efficacy in interference suppression. Additionally, its robustness to sensor calibration errors, with minimal performance degradation even under 10∘ of error, highlights its practical viability for real-world applications. These findings align with and extend prior research, addressing critical limitations in conventional beamforming methods and bridging the gap between theoretical advancements and practical implementations.

The study's implications are significant for fields such as wireless communication, radar, and audio signal processing, where reliable beamforming is essential for enhancing signal quality and suppressing interference. Practical recommendations derived from the findings emphasize the need for robust steering vector estimation in beamforming algorithms to mitigate issues arising from sensor imperfections and interference. Incorporating subspace-based methods, as demonstrated, can significantly enhance interference suppression and improve overall beamforming accuracy. For practical deployment, the algorithm's computational efficiency can be further optimized through hardware acceleration techniques such as parallel processing or the use of field-programmable gate arrays (FPGAs). These optimizations would enable real-time processing capabilities, making the method suitable for dynamic environments such as autonomous vehicles or adaptive radar systems.

Given the algorithm's demonstrated efficacy, its application can be expanded to scenarios involving multiple-input multiple-output (MIMO) systems and large-scale antenna arrays, where the complexity of interference scenarios increases exponentially. Moreover, integrating the proposed method with machine learning models for adaptive parameter tuning could further enhance performance, particularly in rapidly changing environments. Future research should explore hybrid methodologies that combine the strengths of traditional beamforming techniques with modern data-driven approaches to overcome current limitations. Additionally, efforts should focus on extending the algorithm's robustness to handle extreme sensor calibration errors beyond 10∘ and validating its performance in more diverse real-world scenarios, such as urban environments or underwater acoustics.

Practically, organizations and industries adopting beamforming technologies should prioritize robust algorithms like the one proposed in this study to ensure reliable performance under non-ideal conditions. Training personnel in implementing advanced signal processing techniques and maintaining hardware calibration standards are critical for maximizing the utility of such methods. Finally, policymakers and researchers should collaborate to standardize testing protocols for adaptive beamforming systems, ensuring fair performance evaluation and facilitating widespread adoption of cutting-edge methods in the industry.

This study not only advances the field of adaptive beamforming but also provides actionable insights for practitioners and researchers aiming to implement robust signal processing solutions. By addressing key challenges in steering vector estimation and interference suppression, the proposed algorithm lays the foundation for future innovations in high-precision beamforming, with broad applicability across a wide range of domains. The findings underscore the importance of continuous research and development to overcome the challenges posed by complex and dynamic environments, ultimately driving progress in signal processing technologies and their practical applications.

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