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A Hybrid SMI-STAP Approach for Enhanced Sidelobe Cancellation in Radar Systems

Mohammad A. Abdallah[1], Mohammad Nassr[1], Mohammad Anbar[1,2], Hamid Ali Abed AL-Asadi[3*]

[1]Communication Technology Engineering Department, Information and Communication Technology Engineerin College, Tartous University, Syria

[2]Department of Cyber Security Technical Engineering, College of Technical Engineering, Al-Ayen Iraqi University

[3]Department of Computer Science, College of Education for Pure Sciences, University of Basrah, Basrah, Iraq

(*) E-mail:hamid.abed@uobasrah.edu.iq

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ABSTRACT:

Sidelobe Canceller (SLC) systems are critical components in modern radar systems. These systems mitigate interference from unwanted sources or jammers, thereby improving target detection accuracy in both military and civilian applications. However, SLC systems face inherent challenges in multi-jamming scenarios, which degrade the effectiveness of conventional algorithms. This study proposes a hybrid model integrating the Sample Matrix Inversion (SMI) algorithm with Space-Time Adaptive Processing (STAP) to enhance the SLC performance. Simulation results confirm that the combined SMI-STAP approach achieves substantially superior sidelobe interference suppression relative to standalone methods while demonstrating enhanced stability in complex, multi-jamming environments. The hybrid model offers a practical solution to challenges faced by modern radar systems, striking an optimal balance between precision and computational efficiency.

Key words:

Sidelobe Canceller (SLC), Sample Matrix Inversion (SMI) algorithm, Space-Time Adaptive Processing (STAP), Multi-jamming, hybrid model.

RESUMEN:

Only for Spanish speaking authors.

Palabras clave:

REFERENCES AND LINKS / REFERENCIAS Y ENLACES

[1] Z. Song and J. Zhang, "Adaptive side-lobe cancellation technology of modern radar," Aerospace Electronic Warfare, (4) (2021).

[2] P. Priyadarshini and O. C. Vishnu, "Sidelobe canceller system for phased array radar," in Proceedings of IEEE International Radar Symposium, 855–862 (2011).

[3] P. Sedivy, "Radar Sidelobe Canceller Performance Evaluation," in Conference on Microwave Techniques (COMITE), 186–189 (2013).

[4] K. K. Bhat, A. K. Verma and K. P. Ray, "Analysis Of SideLobe Cancellation Algorithm for Practical Implementation," in International Conference on Signal Processing and Integrated Networks (SPIN), 693–697 (2019).

[5] S. Dai, M. Li, Q. H. Abbasi and M. A. Imran, "A Fast Blocking Matrix Generating Algorithm for Generalized SideLobe Canceller Beam former in High Speed Rail Like Scenario," IEEE Sensors Journal 21, 15775–15783 (2021).
[6] M. Anbar, M. Nassr, M. Abdallah, E. Vostorgina, M. Kolistratov and H. A. A. Alasadi, "Sidelobe Canceller Performance Evaluation using Sample Matrix Inversion algorithm," in 4th International Youth Conference on Radio Electronics, Electrical and Power Engineering (REEPE), 1–6 (2022).
[7] Y. Huang, J. Yu, R. Su and C. Li, "A Multi-machine Jamming Method for Side-lobe Cancellation," Journal of Physics: Conference Series 2478, 122076 (2023).
[8] C. A. Balanis, *Antenna Theory: Analysis and Design*, 4th ed. Wiley (2016).
[9] S. A. Vorobyov, "Advances in Robust Adaptive Beamforming," IEEE Signal Processing Magazine 38, 72–85 (2021).
[10] J. Ward, "Space-time Adaptive Processing for Airborne Radar," Tech. Rep. 1015, MIT Lincoln Lab (1994).
[11] W. L. Melvin, "A STAP overview," IEEE Aero. Electron. Syst. Mag. 19, 19–35 (2004).
[12] J. S. Goldstein and I. S. Reed, "Theory of partially adaptive radar," IEEE Trans. Aero. Electron. Syst. 33, 1309–1325 (1997).
[13] J. R. Guerci, *Space-time Adaptive Processing for Radar*. Artech House (2003).

1. Introduction

With the rapid ongoing advancements in modern radar systems, sidelobe canceller (SLC) has emerged as a critical technique to suppress jamming signals infiltrating through the radar's sidelobes. This technology involves integrating low-gain, wide-beam auxiliary antennas alongside the primary antenna or its array. By leveraging the statistical correlation between the jamming signals received by the main and auxiliary channels, the system applies calibrated amplitude adjustments to the auxiliary signals. This generates destructive interference that selectively neutralizes jamming components while preserving the integrity of the target signal [1]. The SLC system has been the focus of multiple investigations across recent studies. Notably, Priyadarshini and Vishnu conducted a comprehensive analysis of its performance, with a particular emphasis on optimizing the weight coefficients assigned to auxiliary antennas. Their research encompassed scenarios with and without active jamming, providing insights into the system's adaptability under varying interference conditions. Furthermore, they expanded their investigation to examine how varying the quantity of auxiliary antennas influences system performance when confronted with multiple simultaneous jammers, offering critical design guidelines for enhanced robustness [2]. In a related investigation, Sedivy assessed the efficacy of the Side-Lobe Cancellation (SLC) system following the removal of natural noise-limiting circuits. The experiment utilized data captured from two distinct radar setups: the first operating in the Very High Frequency (VHF) band and the second in the X-band, both equipped with multi-antenna arrays for full-horizon coverage. The system also incorporated a mobile auxiliary antenna, dynamically synchronized with the main antenna's orientation, engineered to detect and neutralize diverse jamming types through an adaptive SLC mechanism [3]. In a recent study [4], Karan Krisha Bhat et al evaluated the SLC system's performance by analyzing critical metrics such as Jammer-to-Noise Ratio (JNR), angular Direction of Interference (DOI), sampling density, and auxiliary antenna phase alignment. Their findings demonstrated how these factors synergistically enhance cancellation efficiency in diverse jamming environments, emphasizing the importance of synchronizing adaptive processing criteria with practical interference mitigation strategies. Shaowei Dai et al introduced the SZPA algorithm to optimize the Generalized Sidelobe Canceller (GSC). Their polynomial-based approach streamlined the direct generation of column vectors in the Blocking Matrix, significantly reducing computational complexity while maintaining high cancellation accuracy in dynamic jamming environments [5]. In a recent study [6], Anbar et al employed SMI algorithm to analyze the impact of increasing processed pulses on reducing side-lobe levels and the correlation between Interference-to-Noise Ratio (INR) and null depth. Results demonstrated a significant suppression of interference-causing side lobes to approximately -65 dB, identified as the algorithm's maximum null depth. Huang et al. demonstrated in recent scholarship that adaptive side-lobe cancellation (ASLC) systems in radar can be effectively disrupted through a hybrid jamming strategy combining multi-directional and correlated interference[7]. While both SMI and STAP are established techniques, their standalone use presents a trade-off between convergence speed and spatiotemporal discrimination. This work bridges that gap by proposing a novel, cascaded SMI-STAP hybrid framework, specifically designed to tackle multi-jamming scenarios where conventional SLC performance falters. The proposed method analyzes jamming effects based on critical parameters and evaluates system performance under varying interference levels to assess its adaptability in dynamic jamming environments.

2. Methods and Materials

2.a. The Principle Of Sidelobe Cancellation Technology:

The SLC employs the Wiener solution to derive optimal weight vectors through adaptive algorithms that process input signal data. This technique combines adaptively adjusted output channels associatively and subtracts them from unadjusted output channels, thereby isolating desired signals at the system's final output. As illustrated in Fig. 1, the primary channel comprises a high-gain main antenna oriented toward the target signal, which also captures interference and noise via its side lobes. Auxiliary channels, configured with low-gain directional antennas, exclusively receive interference and noise. By adaptively weighting these auxiliary channels, the SLC estimates and suppresses interference within the main channel's side lobes. In conventional radar systems, a directive antenna typically serves as the main channel [8]. This study utilizes a linear array antenna, where the majority of elements form the main channel, and a subset constitutes auxiliary channels (figure 1). Linear arrays are selected for their operational flexibility, high gain, and compatibility with digital beamforming techniques, which enable precise computer-controlled radiation pattern shaping. Such arrays are widely adopted in radar and communication systems due to their scalability and performance advantages. As depicted in Fig. 1, Nm elements are designated as the primary channel, their outputs combined to synthesize the main lobe. The remaining Na auxiliary channels are adaptively weighted using complex coefficients optimized via minimization of interference and noise at the system output. This output is derived by subtracting the weighted auxiliary channel signals from the main channel signal.

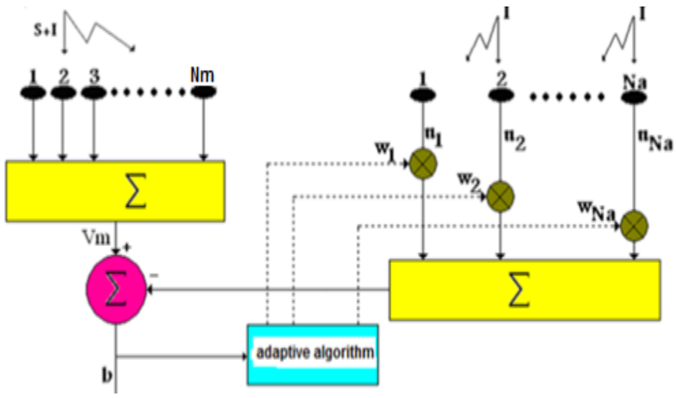

Fig.1. Block diagram of Sidelobe canceller SLC.

This study employs a linear array antenna configuration, where the majority of its elements constitute the main channel, while the remaining subset forms auxiliary channels (Fig. 1). The adoption of linear arrays is justified by their prominence in modern radar systems and their operational advantages, including flexibility in beam steering, high gain, and seamless integration with digital control systems. Furthermore, such arrays enable precise radiation pattern shaping through digital beamforming techniques, enhancing adaptability in dynamic environments. As shown in Fig. 1, the primary channel comprises Nm elements, whose outputs are coherently combined to synthesize the main radiation lobe. In contrast, the Naauxiliary channels are assigned interference suppression tasks through adaptive weighting using complex coefficients. These weights are dynamically optimized by an adaptive algorithm designed to minimize interference and noise at the system's output. The final output is obtained by subtracting the processed auxiliary signals from the main channel signal, effectively isolating the desired target response. Radar systems utilize two primary algorithmic approaches for weight computation: closed-loop (iterative) and open-loop (direct) methods. Closed-loop algorithms achieve high precision through gradual refinement of weights but suffer from slow convergence. Conversely, open-loop algorithms, such as direct matrix inversion, prioritize rapid convergence at the expense of slightly reduced accuracy. This trade-off arises because open-loop methods bypass iterative optimization, relying instead on instantaneous signal statistics [8].

2.b. Sample Matrix Inversion (SMI) Algorithm: Explanation and Key Insights

The SMI algorithm is a direct method for adaptive beamforming in antenna arrays, particularly suited for real-time radar systems due to its rapid convergence. The following section systematically analyzes its theoretical foundations and operational mechanics [9].

2.b.a. System Architecture:

As shown in Fig. 2, The adaptive antenna array model comprises:

M auxiliary elements: These receive input signals denoted as $x_1(n), x_2(n), \ldots, x_M(n)$, each weighted by coefficients $w_1(n), w_2(n), \ldots, w_M(n)$.

1 reference element: The primary antenna output y(n), serving as the desired signal reference.

Objective: Compute the optimal weight vector $w=[w_1, w_2, \ldots, w_M]^T$ to suppress interference while preserving the target signal.

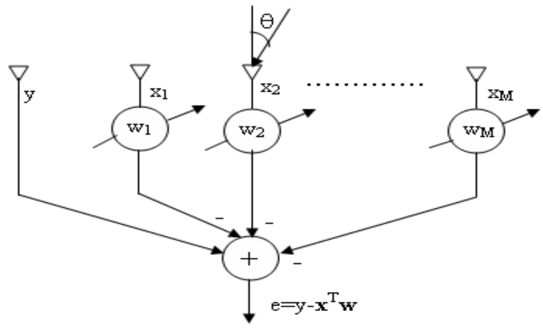

Fig. 2. Adaptive antenna narrow band.

2.b.b. Mathematical Derivation

The SMI algorithm operates through three key steps:

1. Estimation of the Input Correlation Matrix as given in Equation (1).

$$R = \frac{1}{N}\sum_{n=1}^{N} x(n)\, x^H(n) \tag{1}$$

where $x(n)=[x_1(n), x_2(n), \ldots, x_M(n)]T$ is the input vector at the *n-th* snapshot, N is the number of snapshots, and H denotes the Hermitian transpose.

2. Computation of the Cross-Correlation Vector as given in Equation (2).

$$p = \frac{1}{N}\sum_{n=1}^{N} x(n) y^*(n) \tag{2}$$

Where $y^*(n)$ is the complex conjugate of the reference signal.

3. Optimal Weight Calculation as given in Equation (3).

$$W_{opt} = R^{-1}\, p \tag{3}$$

Direct matrix inversion bypasses iterative weight updates, enabling instantaneous convergence.

The input data matrix X(n) is constructed alongside the primary output beam y(n). Through optimization, the weight vector w(n) that minimizes the error signal e(n) is derived. This error signal arises from the aggregation of weighted outputs across the antenna elements, formulated as in Equation (4).

$$e(n) = y(n) - X(n) w^H(n) \tag{4}$$

where $w^H(n)$ denotes the Hermitian transpose of the weight vector, and X(n) represents the multi-channel input data matrix

Block diagram of the adaptive radiation beam problem based on SMI algorithm is shown in Fig. 3.

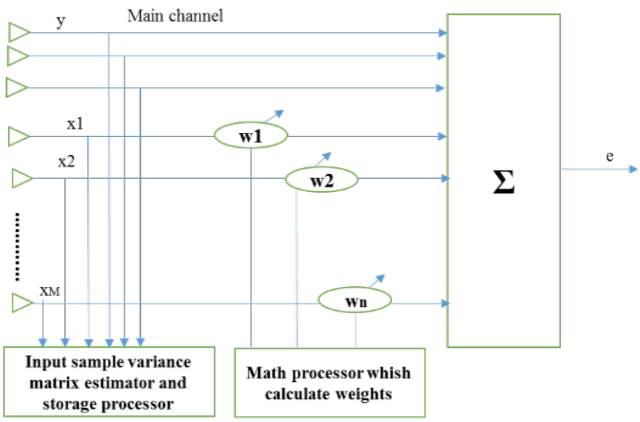

Fig.3. Adaptive open-loop system using SMI algorithm.

2.c. Space-time adaptive processing (STAP)

Space-time adaptive processing (STAP) constitutes a pivotal methodology in airborne radar systems, renowned for its exceptional efficacy in mitigating ground clutter and enhancing target detection performance [10][11]. By leveraging multidimensional signal processing across spatial and temporal domains, STAP algorithms achieve enhanced spatial-temporal resolution, precise parameter estimation, and superior detection capabilities in heterogeneous environments [11]. However, practical implementation faces three principal challenges: (1) excessive reliance on large training datasets for covariance matrix estimation, (2) prohibitive computational demands due to high-dimensional matrix operations, and (3) sensitivity to non-stationary clutter and array imperfections in real-world scenarios. Consequently, advancing adaptive methodologies that balance low sample support, computational efficiency, and robustness to environmental uncertainties remains a critical research frontier for next-generation radar systems.

In a side-looking airborne pulsed Doppler radar system employing a uniform linear array (ULA) of M receive elements, the acquired signal measurements are organized into a three-dimensional data matrix of dimensions N×M×L. Here, N denotes the number of coherent pulse bursts transmitted at a fixed pulse repetition frequency (PRF fr), and L represents the range cell count. A space-time snapshot—defined as a two-dimensional cross-section of the data matrix along the range dimension under target-free conditions is mathematically represented as an NM-dimensional column vector, formulated as in Equation (5).

$$X = X_c + X_j + X_n \tag{5}$$

In this context, Xc, Xj, and Xn represent the clutter, jamming, and thermal noise components, respectively. Given prior knowledge of the target's spatial and Doppler frequency parameters, a widely adopted STAP filter architecture is the Generalized Sidelobe Canceler (GSC), which transforms the filtering task into the constrained optimization problem given in Equation(6) [12].

$$\min_{w} J(w) = \min_{w} E\,[\|d - w^H z\|_2^2] \tag{6}$$

Here, the operators min, E [.],$\|.\|_2$, and the superscript H correspond to the minimum value of an objective function, statistical expectation operator, Euclidean norm, and Hermitian transpose, respectively. The scalar $d = s^H x$ quantifies the main beam output, where s is the NM×1 space-time steering vector aligned with the target's Doppler frequency f_d^t and spatial frequency f_s^t. The noise-subspace projection $z = T^H x$ yields a (NM−1)×1 vector, with T being an NM×(NM−1) blocking matrix constructed from an orthogonal basis spanning the null space of s. The adaptive weight vector w, of dimensions (NM−1)×1, is optimized to suppress interference. The steering vector s is defined in Equation (7)[13].

$$s = v_d(f_d^t) \otimes v_s(f_s^t) \tag{7}$$

Where $\otimes$ represents the Kronecker product, and the $N * 1$ vector $v_d(f_d^t)$ and $M * 1$ vector $v_s(f_s^t)$ denote the target's temporal and spatial steering vectors, respectively. More pre-cisely, they are given as in Equations (8) and (9) [3.

$$v_d(f_d^t) = [1, \exp(j2\pi f_d^t), \dots \dots . \exp(j2(N-1)\pi f_d^t)]^T \tag{8}$$

$$v_s(f_s^t) = [1, \exp(j2\pi f_s^t), \dots \dots . \exp(j2(M-1)\pi f_s^t)]^T \tag{9}$$

Respectively, where superscript T denotes the transposition operation.
By solving the minimisation problem Equation (2), the optimal weight vector can be obtained as in Equation (10).

$$W_{opt} = R_z^{-1} r_{zd} \tag{10}$$

Where $(.)^{-1}$ is the matrix inversion, $R_z = E[zz^H] = T^H RT$, $R = E[xx^H]$, and $r_{zd} = E[zd^*] = T^H Rs$ with $(.)^*$ denoting the complex conjugation operator.

2.d. Experiment setup:
The performance of the proposed Hybrid SMI-STAP approach is evaluated through the following structured methodology, outlining the simulation framework and parameters:

2.d.a. Key Parameters:

- Number of ULA elements: M=16.
- Coherent processing interval (CPI): N=32 pulses.
- Pulse repetition frequency (PRF): fr=10kHz.
- Signal-to-noise ratio (SNR): SNR = 20dB.
- Number of Auxiliary Channels (N_a): Na = 4
- Jammer-to-Noise Ratio (JNR): JNR = 30 dB
- Adaptation Rate (μ): μ=0.01 (controls weight update speed).
- Blocking Matrix Type: SVD-based (Singular Value Decomposition)
- Fusion Ratio (α): α=0.7 (weighting factor for SMI/STAP fusion).
- Diagonal Loading Factor (γ): $\gamma=0.1\sigma n^2$ (noise-dependent stabilization).

2.d.b. Proposed Hybrid SMI-STAP Architecture and Weight Computation
The core innovation of this work lies in the strategic fusion of the SMI and STAP algorithms within the SLC structure. Rather than a simple summation of weights, a cascaded two-stage processing framework has been proposed and designed to leverage the distinct strengths of each algorithm

- **Stage 1: SMI-Based Coarse Suppression**

  This stage employs SMI algorithm to perform an initial and rapid cancellation of high-power jammers that enter through the sidelobes. Using the auxiliary channels, the optimal weight vector W_{SMI} is computed directly via the sample matrix inversion (Eq. 3). This stage acts as a pre-filter, effectively creating deep nulls in the directions of the most prominent jammers.

- **Stage 2: STAP-Based Fine-Grained Nulling**

  The residual signal, after SMI processing, is fed into the STAP processor. The STAP stage calculates its optimal weight vector W_{STAP} (Eq. 10) to suppress interference that the SMI stage cannot completely eliminate.

- **Hybrid Weight Synthesis and Stabilization**

Final output of the system is generated by the cascaded application of both processors. However, to formulate a unified hybrid weight for analysis and to ensure system stability, a composite weight vector is synthesized. This synthesis is performed after computing both W_{SMI} and W_{STAP} independently based on the estimated covariance matrix R as given in Equation(11).

$$W_{Hybrid} = \alpha W_{SMI} + (1-\alpha)T^H W_{STAP} \tag{11}$$

Where α is the fusion ratio, T is the blocking matrix from the STAP GSC structure, and T^H represents the STAP weights into an appropriate subspace for integration. To mitigate numerical instability, diagonal loading is employed. The stabilized matrix is given by $R_{DL}=R+\gamma I$, where $\gamma=0.1\sigma n^2$ is the diagonal loading factor and I is the identity matrix. This enhances the robustness of both the SMI and STAP weight calculations.

3. SIMULATION RESULTS AND EVALUATION

Simulation of the proposed SLC hybrid method has been performed with the existing of interference and without the existing of interference for several scenarios as follows:

3.a. Scenario 1:

In this scenario, the SMI algorithm has been applied to the SLC system with three jammers positioned at a 60, -60 and 30 degree angle ($\theta_{j1} = 60^0, \theta_{j2} = -60^0, \theta_{j3} = 30^0$). A comparative analysis has been conducted before and after the implementation of the SMI algorithm. The results have been shown in Fig. 4.

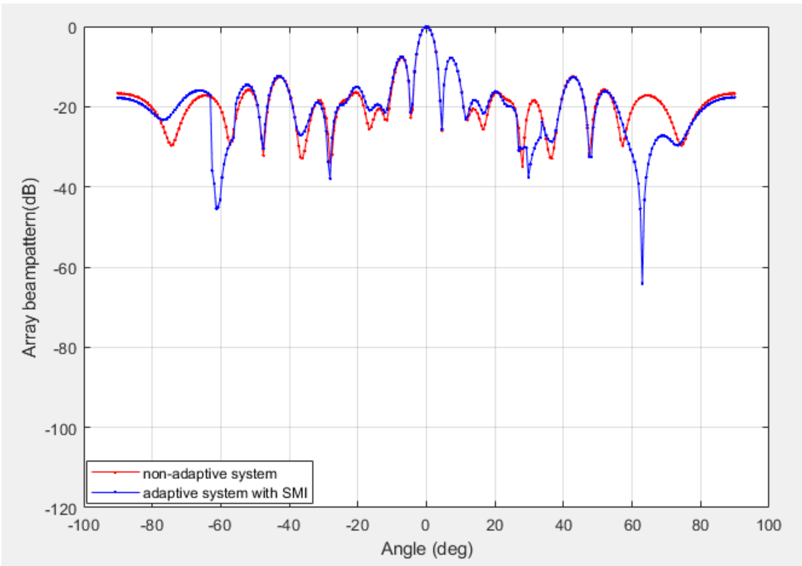

Fig. 4. Comparison between sidelobe canceller in non-adaptive system and adaptive system with SMI in case three jammers ($\theta_{j1} = 60^0, \theta_{j2} = -60^0, \theta_{j3} = 30^0$)

As shown in Fig. 4 following the implementation of the SMI algorithm, the side lobe level in the direction of the first jammer has been reduced to -65 dB, while the performance in the direction of the second jammer degraded to -45 dB and the performance in the direction of the third jammer degraded to -37 dB.

3.b. Scenario 2:

In this scenario, the hybrid SMI-STAP framework was implemented in the SLC system to mitigate three angularly distributed jammers positioned at θ_j = 60°, −60°, and 30°. As shown in Fig. 5, the hybrid algorithm exhibited graded interference suppression performance, reducing sidelobe levels to -80 dB toward θ_j = 60°, -65 dB toward θ_j= −60°, and -58 dB toward θ_j= 30°. The performance disparity stems from variations in spatiotemporal interference dynamics among the jammers and the algorithm's ability to prioritize signal discrimination through hierarchical adaptive filtering. These results confirm the hybrid framework's efficacy in managing multi-source interference, particularly under spatially asymmetric and spectrally overlapping jamming conditions.

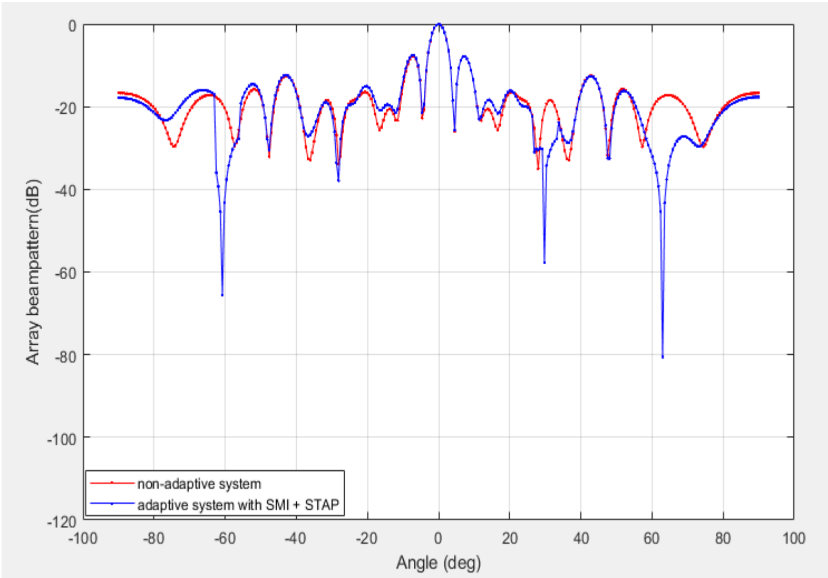

Fig.5. Comparison between sidelobe canceller in non-adaptive system and adaptive system with SMI + STAP in case three jammers ($\theta_{j1} = 60^0, \theta_{j2} = -60^0, \theta_{j3} = 30^0$)

Table 1 provides a quantitative comparison of interference suppression performance between the conventional SMI algorithm and the proposed hybrid framework. A significant improvement of −21 dB in sidelobe cancellation level is observed for the third jammer, demonstrating the hybrid technique's enhanced robustness in high-interference environments. This substantial suppression gain validates the framework's efficacy in maintaining signal integrity under extreme spectral-spatial interference conditions, achieving near-complete nulling of jamming sources.

Table 1: Performance comparison between the SMI algorithm and the proposed hybrid technique

Number of jammers	SMI	SMI+STAP	Interference suppression improvement level
Jammer 1	-65dB	-80dB	-15 dB
Jammer 2	-45dB	-65dB	-20 dB
Jammer 3	-37dB	-58dB	-21 dB

3.c. Scenario 3:

In this scenario, the hybrid SMI-STAP framework was implemented in the SLC system to counteract five high-power jammers distributed In the range $\theta_j = [30, 60]$. A comparative analysis of system performance, as depicted in Fig. 6, reveals stark contrasts between the hybrid approach and standalone SMI. While the conventional SMI algorithm exhibits severe degradation in interference suppression declining from -65 dB to -30 dB under intensified jamming, the hybrid technique demonstrates gradual yet superior resilience, maintaining suppression levels from -80 dB (initial) to -45 dB even in extreme jamming conditions. This graded performance underscores the hybrid framework's ability to dynamically adapt to spatially dense and spectrally overlapping interference through multi-dimensional covariance optimization and STAP-augmented spatiotemporal filtering. The results affirm the hybrid method's exceptional efficacy in robust jamming environments, achieving a 35 dB performance margin over SMI at peak interference.

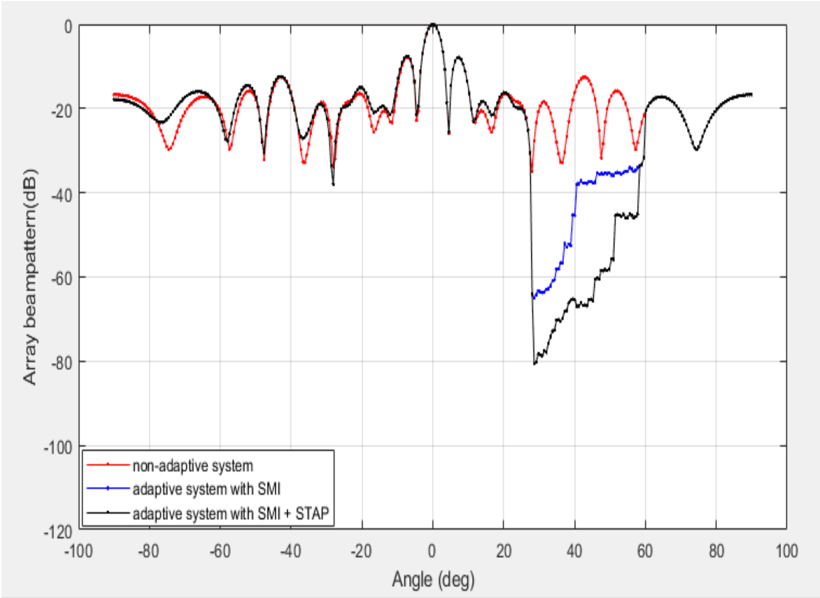

Fig. 6. Comparison between sidelobe canceller in non-adaptive system and adaptive system with SMI + STAP in case five jammers (θj=[30,60])

4. Conclusion and Recommendations

In conclusion, this research has introduced and validated a hybrid SMI-STAP framework that significantly enhances SLC performance in multi-jamming environments. The cascaded architecture, combining coarse SMI suppression with fine-grained STAP filtering, demonstrated a remarkable improvement of up to 21 dB in sidelobe cancellation over the conventional SMI approach. This enhancement is attributed to the synergistic integration of STAP's spatiotemporal filtering and SMI's covariance matrix optimization, enabling precise signal isolation in complex jamming environments. However, the proposed framework requires computational efficiency improvements for real-time applicability. For future work, we plan to investigate the integration of machine learning techniques such as recurrent neural networks for predictive covariance matrix estimation to further reduce computational latency. Additionally, we will explore the development of lightweight, quantized versions of the hybrid algorithm suitable for deployment on FPGA and SoC platforms, targeting real-time operation in resource-constrained embedded radar systems.

