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Performance Analysis of Adaptive Beamforming Algorithm for Smart Antenna in Wireless Communications

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Abstract

A smart antenna is an innovative compatibility of antenna array elements and signal-processing algorithm to achieve maximum spectral efficiency and capacity in wireless communication networks. This technique consists of an adaptive antenna array that continuously adjusts its radiation characteristics (main lobe beam-width, side lobe levels, and zero-point function) to provide a narrow beam in the direction of the desired signal arrival and to establish zero points in the direction of interference, thus ensuring the highest signal to interference and noise ratio (SINR).

Adaptive beamforming is an effective method for improving spatial selectivity in smart antenna systems operating in interference-prone wireless environments. This paper presents a simulation-based study of the least squares (LMS) algorithm using a uniform linear array (ULA) in the presence of both signal of interest and interference signals. A MATLAB-based simulation model is developed to analyze the adaptive behavior of the beamformer under various scenarios. The evaluation is conducted using matrix operator responses, mean squared error (MSE), adaptive weight evolution, and desired signal tracking. The results demonstrate the ability of the LMS algorithm to achieve adaptive spatial filtering with stable convergence and reliable interference mitigation.

Keywords: Smart antenna, adaptive beamforming, inter-symbol Interference (ISI), Least Mean Squares (LMS) Algorithm.

تحليل أداء خوارزمية تشكيل الحزمة التكيفية للهوائي الذكي في الاتصالات اللاسلكية

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الملخص:

الهوائي الذكي هو تقنية مبتكرة تجمع بين عناصر مصفوفة الهوائي وخوارزمية معالجة الإشارة لتحقيق أقصى كفاءة طيفية وسعة في شبكات الاتصالات اللاسلكية. تعتمد هذه التقنية على مصفوفة هوائي تكيفية تُعدّل باستمرار خصائص إشعاعها (عرض حزمة الفص الرئيسي، ومستويات الفصوص الجانبية، ودالة نقطة الصفر) لتوفير حزمة ضيقة في اتجاه وصول الإشارة المطلوبة، وإنشاء نقاط صفرية في اتجاه التداخل، مما يضمن أعلى نسبة إشارة إلى تداخل وضوضاء (SINR)..

يُعدّ تشكيل الحزمة التكيفي طريقة فعّالة لتحسين الانتقائية المكانية في أنظمة الهوائيات الذكية العاملة في بيئات لاسلكية مُعرّضة للتداخل. تُقدّم هذه الورقة دراسة قائمة على المحاكاة لخوارزمية المربعات الصغرى (LMS) باستخدام مصفوفة خطية منتظمة (ULA) في وجود كلٍّ من الإشارة المطلوبة وإشارات التداخل. تم تطوير نموذج محاكاة قائم على MATLAB لتحليل السلوك التكيفي لمُشكّل الحزمة في ظل سيناريوهات مختلفة. أُجري التقييم باستخدام استجابات مُعامل المصفوفة، ومتوسط مربع الخطأ (MSE)، وتطور الوزن التكيفي، وتتبع الإشارة المطلوبة. تُظهر النتائج قدرة خوارزمية LMS على تحقيق ترشيح مكاني تكيفي مع تقارب مستقر وتخفيف موثوق للتداخل.

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الكلمات المفتاحية: هوائي ذكي، تشكيل الحزمة التكيفي، تداخل الرموز (ISI)، خوارزمية المربعات الصغرى (LMS).

I. Introduction

In modern wireless communication systems, smart antenna technology has emerged as a pivotal solution to enhance system performance, channel capacity, coverage, and spectrum efficiency. By utilizing efficient spatial signal processing, these advanced array systems can identify distinct spatial signatures and compute optimal beamforming vectors for precisely tracking receivers. Fundamentally, beamforming operates by applying complex weight vectors adjusting both the magnitude and phase to the signal at each antenna element. This adaptive spatial filtering dynamically steers the main radiation lobe toward the desired user while simultaneously placing deep spatial nulls in the directions of co-channel and inter-channel interferers [1]. By continuously adapting to time-varying propagation environments, smart antennas maximize directional gain and suppress unwanted emissions, thereby significantly enhancing overall network capacity and link reliability [2]. When the angles of arrival (AOA) or Direction of Arrival (DOA) of the desired signals fluctuate over time, the complex weights of the incoming signals must be adjusted iteratively; a paradigm known as adaptive beamforming. These adaptive algorithms operate based on prescribed performance criteria such as Minimum Mean Square Error (MMSE), Maximum Signal to Interference plus Noise Ratio (SINR), Maximum Likelihood (ML), Minimum Noise Variance, and Maximum Gain, and are mathematically implemented through a set of recursive equations. Adaptive algorithms are generally classified into two main categories: blind and non-blind. Blind algorithms estimate optimal composite weights without any prior knowledge of transmission characteristics. In contrast, non-blind algorithms rely on a known reference or experimental signal to detect the desired user and dynamically update the composite weight vectors. A prominent example of a non-blind construct is the Least Mean

Squares algorithm (LMS) [2], which forms the basis of the inter-symbol interference mitigation (ISI) optimization framework used in this study. This study examines the application of an adaptive beamforming system based on the LMS algorithm using a regular linear antenna array. It focuses on the mathematical formulation of the adaptive updating mechanism of the LMS algorithm and its role in directing the beam towards the desired user while minimizing interference from competing sources.

The proposed framework aims to demonstrate how adaptive beamforming can significantly improve spatial selectivity and communication performance in dynamic wireless environments.

II. Smart antenna

Unlike conventional fixed-pattern configurations, the smart antenna integrates a multi-element array with advanced digital signal processing (DSP) to dynamically adapting its radiation pattern [3]. Through continuous analysis of the statistical characteristics of the received signals, this architecture improves the wireless link by precisely isolating the signal of interest (SOI) from multipath interference and inter-channel interference. Figure (1) illustrates the functional block diagram of this adaptive spatial filtering mechanism.

This operational architecture is implemented in three sequential stages: (i) estimating the arrival direction of all incoming waves, (ii) classifying the incoming spatial sources to isolate the desired signal from interference sources in the same channel, and (iii) adaptively updating the composite weight vectors using a beamforming algorithm. In doing so, the architecture dynamically directs the main beam towards the desired signal, while generating deep spatial zero points in the interference and noise directions, thereby increasing the signal to interference noise ratio (SINR) and the overall network capacity [4].
Depending on operational constraints and processing complexity, smart antenna architectures are generally classified into switched beam topologies and adaptive array topologies. Switched beam topologies use a limited set of predefined directional beam patterns,

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selecting the discrete beam that provides optimal receive power. While computationally efficient, this approach lacks the tracking capability required for highly dynamic channels.

In contrast, adaptive arrays continuously optimize radiation characteristics in real time to counteract noise, inter-channel interference, and severe multipath vanishing.

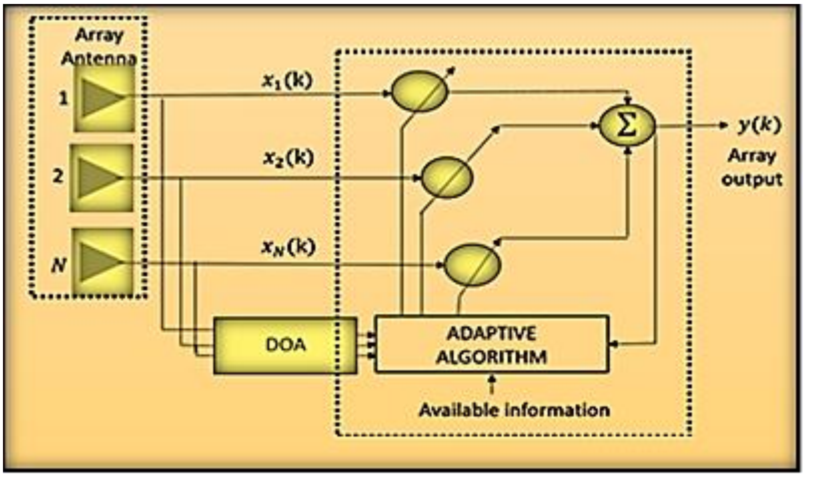

Figure 1. Block diagram of smart antenna

By employing iterative estimation algorithms, adaptive arrays maximize directional gain toward the target signal source, while precisely generating deep spatial zero points in the directions of inter channel interference sources. This real-time spatial filtering forms the basis of the interference mitigation framework investigated in this study [4,5].

To analyze the spatial processing mechanism of the smart antenna system, we consider a uniform linear array (ULA) consisting of (M) identical and equidistant radiation elements separated by a distance (d = λ/2), where (λ) is the wavelength of the carrier wave. Assuming a far-field propagation environment, let a complex baseband signal x(k) from the desired user impinge upon the array from a time-varying spatial angle (θ). Concurrently, the array is subjected to (i) co-channel interfering signals, i_n(k) (for n = 1, 2, …, i), arriving from distinct angular directions θ_n. The total spatial snapshot vector

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S(k) ∈ $\mathbb{C}^{Mo\times 1}$ received by the array at any discrete time instant (k) is mathematically formulated as:

$$s(k) = a(\theta)\, x(k) + \sum_{n=1}^{I} a(\theta_n) i_n(k) + v(k) \qquad (1)$$

where $v(k) \in \mathbb{C}^{Mo\times 1}$ denotes the zero-mean Additive White Gaussian Noise (AWGN) vector with variance σ^2, and $a(\theta) \in \mathbb{C}^{Mo\times 1}$ represents the array steering vector that defines the spatial phase shift across the elements, expressed as:

$$\mathrm{a}(\theta) = \left[\,1, e^{-j\pi\sin(\theta)}, e^{-j2\pi\sin(\theta)}, \ldots\ldots, e^{-j(M-1)\pi\sin(\theta)}\right]^T \qquad (2)$$

The composite output of the smart antenna system, y(k), is synthesized via a linear combination of the received signal vector and a complex weight vector $\mathrm{w} = [\,w_1, w_2, \ldots\ldots w_M]^T$, which yields:

$$y(k) = \mathrm{W}^H\, x(k) \qquad (3)$$

While this fixed formula establishes a baseline for spatial filtering, non-fixed channels necessitate the use of time-varying weights $w(k)$ to track angular fluctuations [5]. Therefore, real-time optimization is crucial for maintaining an optimal signal-to-interference and noise ratio in the face of temporal distortions caused by multipath propagation.

III. Inter symbol interference

In mobile wireless communication environments, spatial dispersion and the movement of the transmitter and receiver result in a dynamic, linearly time-varying multipath channel. The resulting superposition of attenuated, phase-change, and time-delayed signals causes rapid envelope fluctuations and strong destructive interference, defining the fundamental physical boundary of symbol interference (ISI). Thus, if $x(k)$ represents the transmitted signal

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and $y(k)$ represents the received signal, the input-output relationship can be mathematically formulated as follows [5]:

$$y(k) = h(0)x(k) + h(1)x(k-1) + v(k) \qquad (4)$$

Where $h(0), h(1)$ denotes the fading channel coefficient at time $k, k-1$, and $v(k)$ represents the Additive White Gaussian Noise (AWGN).

It is evident from the equation (4), it can be observed that the output at time (k) is influenced not only by the instantaneous input $x(k)$ but also by the memory of the past symbol $x(k-1)$. This temporal dependency indicates that the preceding symbol introduces inter-symbol interference (ISI) into the current symbol, this signifies that $x(k-1)$ is interfering with $x(k)$.

In general:

$$\begin{aligned} y(k) = h(0)\,x(k) + h(1)x(k-1) + h(2)x(k-2) + \cdots \\ + h(L-1)x(k-L+1) + v(k) \end{aligned} \qquad (5)$$

The system output is governed by equation (5), where $h(0), h(1), ., h(L-1)$ represent the channel taps (L channel taps), it is observed that as L increases, the (ISI) is further exacerbated. This behavior occurs because a larger number of preceding symbols overlap and interfere with the current symbol.

Symbols are linearly combined to mitigate the effects of (ISI).

$$y(k+2) = h(0)x(k+2) + h(1)x(k+1) + v(k+2) \qquad (6)$$

$$y(k+1) = h(0)x(k+1)h(1)x(k) + v(k+1) \qquad (7)$$

$$y(k) = h(0)x(k) + h(1)x(k-1) + v(k) \qquad (8)$$

By expressing these equations in vector form, we obtain:

$$\begin{bmatrix} y(K+2) \\ y(k+1) \\ y(k) \end{bmatrix} = \begin{bmatrix} h(0) & h(1) & 0 & 0 \\ 0 & h(0) & h(1) & 0 \\ 0 & 0 & h(0) & h(1) \end{bmatrix} \begin{bmatrix} x(k+2) \\ x(k+1) \\ x(k) \\ x(k-1) \end{bmatrix} + \begin{bmatrix} v & (k+2) \\ v & (k+1) \\ v & (k) \end{bmatrix}$$

$$Y = HX + V \tag{9}$$

Assuming the combining weights are given by w_0, w_1, and w_2, the equalizer weight vector can be defined as:

$$w = \begin{bmatrix} w_0 \\ w_1 \\ w_2 \end{bmatrix}$$

$$W = w_0\, y(k+2) + w_1 y(k+1) + w_2 y(k) \tag{10}$$

This weighted linear combination of the outputs $y(k), y(k+1)$, and $y(k+2)$ is performed to mitigate the interference, which can be expressed as:

$$\hat{X}(k) = w^T y(k) \tag{11}$$

Where $\hat{X}(k)$ represents the estimated symbol after equalization, and $y(k) = [y(k) + y(k+1) + y(k+2)]^T$ is the output vector.

This vector-based matrix formula provides a precise mathematical description of the shared space-time channel properties that cause code interference.

IV. Adaptive Beamforming

The array factor (AF) of a uniform linear array (ULA) consisting of (M) equally spaced antenna elements (d) receiving signals from multiple spatial directions can be represented as follows:

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$$AF(\theta) = \sum_{m=0}^{M-1} w_n * e^{\left(jn\left(\frac{2\pi d}{\lambda}\cos\theta+\beta\right)\right)} \qquad (12)$$

Where (β) is the inter element phase shift and it is equal to $(\frac{-2\tau d}{\lambda_0} cos\theta_0)$, and (θ_0) denotes the target spatial angle representing the desired direction of the propagated beam.

The adaptive beamforming process typically consists of four main stages:

- The antenna array receives signals from the desired user and interference sources.
- The received signals are linearly combined using a set of composite weights.
- An adaptive optimization algorithm evaluates the system's performance using an error criterion.
- The weight vector is repeatedly updated to improve the beamformer's response.
- This closed-loop adaptive mechanism enables the system to continuously track changes in channel conditions and user locations [6,7].

To overcome the matrix inversion problem, iterative techniques such as LMS and RLS algorithms are widely used [7]. Although RLS offers faster convergence, LMS remains highly attractive for practical wireless infrastructure due to its simpler computational requirements and high algorithmic efficiency [8]. Crucially, this low-complexity framework enables real-time tracking of rapid angular fluctuations caused by user movement, a vital capability for ensuring reliable spatial processing in ultra-dense and volatile 5G and beyond networks [9].

V. Least Mean Squares (LMS) Algorithm

The least squares (LMS) algorithm is a non-blind adaptive approach based on a known training or reference signal. Employing

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a gradient-based faster regression method, the algorithm uses an iterative procedure to apply successive corrections to the weighting vector. Moving in the direction of the negative gradient vector, the algorithm systematically converges towards the minimum mean squared error (MMSE). A key advantage of the LMS algorithm is its relative computational simplicity, as it eliminates the need for correlation function calculations and matrix inversions [8,10].
As illustrated in Figure (2), the outputs of each sensor are individually adjusted according to their corresponding weights and then linearly combined. This optimization process fine-tunes the antenna array to achieve maximum gain in the direction of the desired signal, while simultaneously positioning zero-signal points in the direction of interference sources.

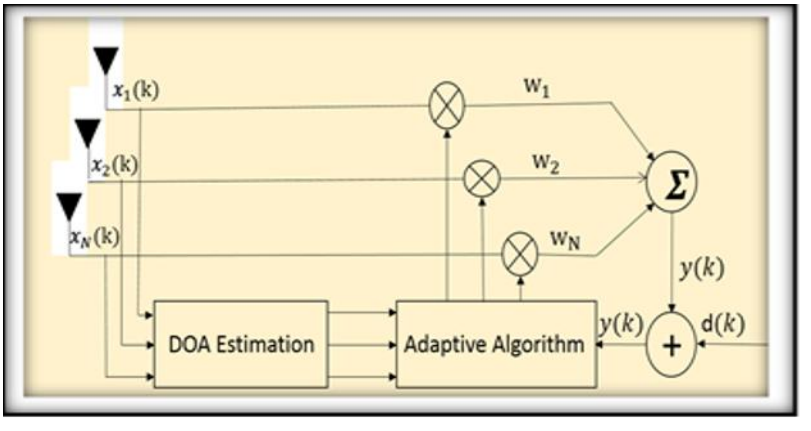

Figure 2. Smart Antenna Array System using LMS Algorithm

The output of a uniform linear array (ULA), denoted as y(k) at any discrete time k, is defined by the linear combination of the input vector x(k) and the weight vector w(k), as follows:

$$y(k) = \mathrm{W}^H(k)\, x(k) \tag{13}$$

Where $w(k) = [w_1 + w_2 + \cdots + w_N]^H$ and $x(k) = [x_1 + x_2 + \cdots + x_N]$.

The error signal $e(k)$, is the difference between the desired signal $d(k)$ and the output of a uniform linear array $y(k)$.

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$$e(k) = d(k) - y(k) \tag{14}$$

By bypassing computationally intensive matrix inversions, the LMS algorithm uses the instantaneous gradient vector of the cost function, denoted as (∇J(k)), to update the weights vector. Based on the Faster Regression framework, the equation for updating the weights vector w(k+1) at time k+1 is formulated as follows:

$$w(k+1) = w(k) + \frac{1}{2}\mu[-\nabla \mathrm{J(k)}] \tag{15}$$

Where: J(n) = E[|e(k)|^2] represents the mean squared error (MSE) cost function, and μ denotes the step-size coefficient, which controls the convergence rate and stability of the algorithm.

To ensure the stability of the MSE and the convergence of the adaptive process, the step-size coefficient must strictly satisfy the following finite condition $0 < \mu < \frac{1}{\lambda max}$,Where λ_{max} is the maximum eigenvalue of the autocorrelation matrix of the input signal R.

Calculating the instantaneous gradient vector ($\nabla J(k)$) requires both the autocorrelation matrix (R) and the cross-correlation vector (r).

These two quantities can be determined using

$$\nabla J(k) = -2r(k) + 2R(k)w(k) \tag{16}$$

Where:

$$R(k) = x(k)\, x^H(k) \tag{17}$$

$$r(k) = d^*(k)\, x(k) \tag{18}$$

The optimal weight vector can be obtained by inserting equations (16), (17), and (18) into (15).

$$w(k+1) = w(k) + \mu[r(k) - R(k)\, w(k)] \tag{19}$$

$$w(k+1) = w(k) + \mu\, x(k)[d^*(k) - x^H(k)w(k)] \tag{20}$$

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Therefore, the LMS cycle at every step of the time (k) can be created as

$$w(k+1) = w(k) + \mu\, x(k) e^{*}(k) \tag{21}$$

The performance and convergence behavior of the LMS algorithm is mainly controlled by three key factors: the step size parameter (μ), the candidate rank (number of weights), and the spectrum of eigenvalues of the input data correlation matrix.

VI. Simulation Results and Discussion

For simulation purposes, MATLAB is used to accurately evaluate the performance of the adaptive beamforming algorithm using least-squares principles. A comprehensive numerical simulation is performed using a regular linear array of 10 elements, spaced at a uniform distance (0.5λ), with a noise variance of $\sigma^2 = 0.001$, and the adaptive step size coefficient is calculated from the equation $\mu = \frac{1}{2*real(trace(R))}$ to achieve optimal balance. This evaluation defines the key operational metrics of the beamformer, focusing on amplitude responses analysis; mean squared error convergence rates (MSEs), absolute weight paths, and real time signal tracking capabilities.

Figures (3, 4, 5) illustrates the matrix coefficient responses of the adaptive LMS algorithm in various evaluation scenarios demonstrating the spatial filtering capability of the adaptive processor in a multi-interfering shared channel environment.

In Figure (3), the signal of interest arrives at a directional angle of 30° while simultaneously being obscured by an interference source at an angle of - 60°. In Figure (4), the number of interference signals is increased at angles of - 60° and 55° to investigate the algorithm's interference suppression capabilities. In Figure (5), the interference environment is increased at angles of -60°, 55°, and 0°, and the number of signals of interest is also increased, arriving at two directional angles of 30° and -30° to evaluate the beamformer's ability to capture multiple signals of interest simultaneously.

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In Figure (4), the matrix coefficient response shows that the main beam remains precisely oriented in the direction of interest, while deep zeros are formed in the interference directions. As the number of interference signals increases, the beamformer efficiently maintains the signal of interest while adapting its spatial response to suppress additional interferences.

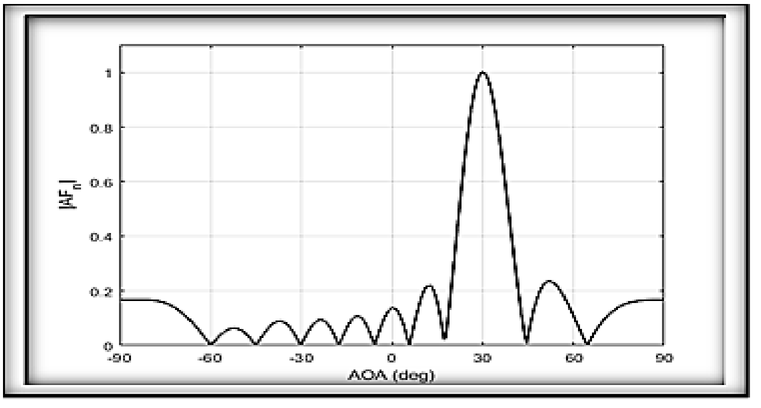

Figure 3. Amplitude responses using the adaptive LMS algorithm for Signal of Interest at 30° in the presence of two interference at -60° .

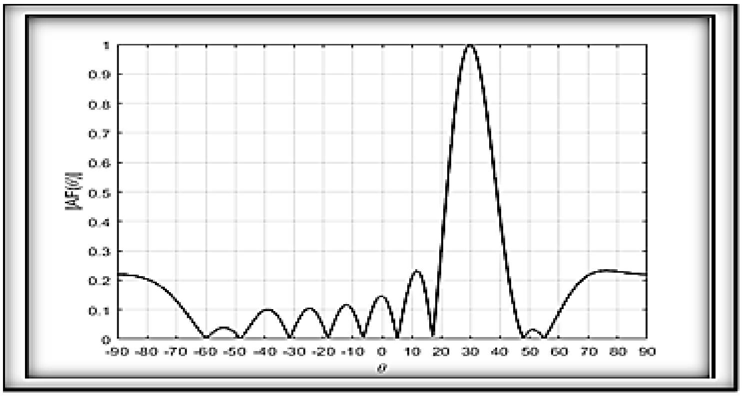

Figure 4. Amplitude responses using the adaptive LMS algorithm for Signal Of Interest at 30° in the presence of two interference at -60° and 55°.

In Figure (5), the results show that the beamformer successfully forms multiple main lobes in the directions of the signal of interest while maintaining effective suppression of interference signals. Although the spatial response becomes more complex with the introduction of additional signals of interest, the algorithm maintains good beam-orienting performance without compromising its interference reduction capabilities.

These results demonstrate the power of the adaptive LMS algorithm in maintaining reliable reception of the signal of interest under increasing interference conditions. This confirms the effectiveness of adaptive LMS algorithm in supporting many users in wireless communication environments.

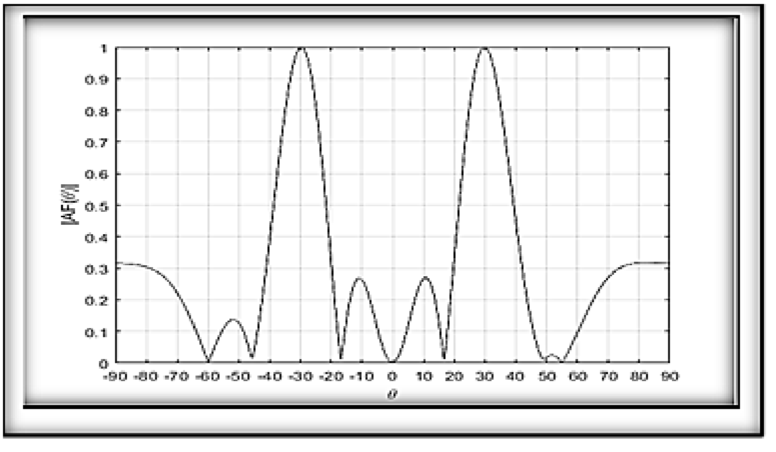

Figure 5. Amplitude responses using the adaptive LMS algorithm for Two Signals of Interest at 30° and -30° in the presence of three interference signals at -60°, 55° and 0°.

Figure (6) illustrates the convergence and stability behavior of the adaptive LMS algorithm, where the mean squared error (MSE) curve is shown versus several iterations. The MSE exhibits relatively high values during the initial iterations due to the random initialization of the adaptive weight vector and the temporary adaptation process. As the iterations progress, the error rapidly decreases, indicating that the algorithm is effectively updating the matrix weights toward the optimal solution. After approximately 10 iterations, the MSE reaches a low and nearly constant level with only minor fluctuations, demonstrating stable convergence.

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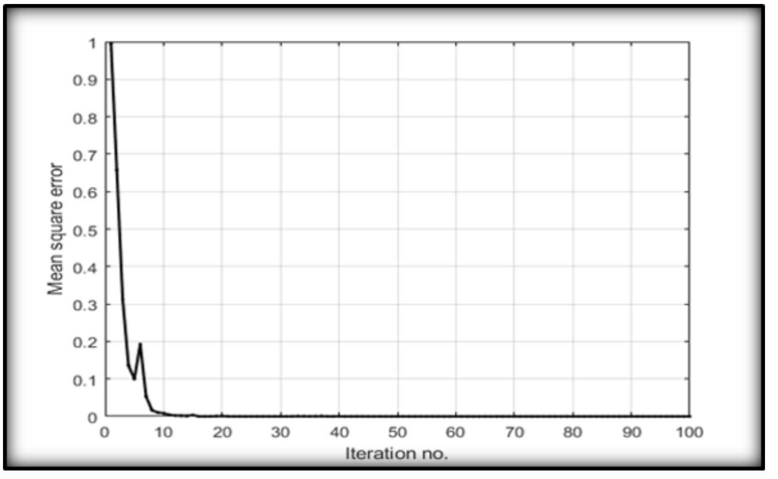

Figure 6. Mean squared error versus number of iterations obtained using the adaptive LMS algorithm

Figure (7) represents the evolution of the adaptive weight values during the LMS algorithm's learning process. With each iteration, the weight coefficients exhibit significant changes as the algorithm continuously updates the matrix weights to minimize estimation error. As the adaptation process progresses, the weight values gradually converge and become nearly constant after approximately 20 iterations, indicating that the algorithm has reached a stable operating state.

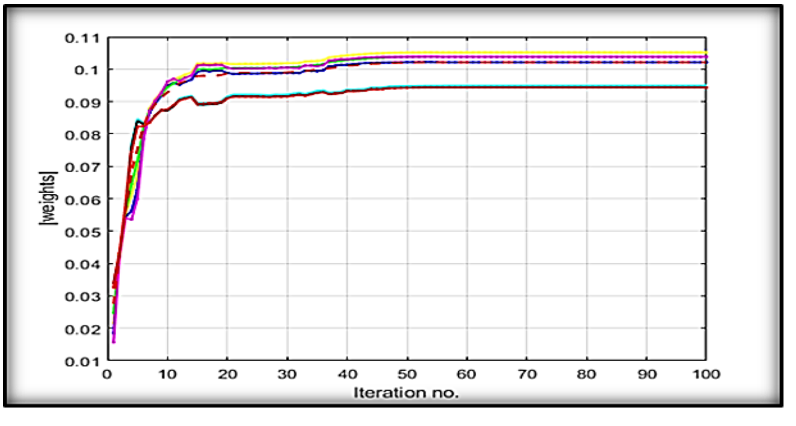

Figure 7. Convergence of adaptive weights using the adaptive LMS

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These results demonstrate that the LMS algorithm effectively adapts the matrix coefficients and achieves stable convergence, enabling precise beam routing and reliably suppressing interference.

Figure (8) illustrates the comparison of the signal of interest with the array output over 100 iterations. At the beginning of the signal of interest tracking process, a significant difference appears between the signal of interest and the array output due to the initial weight adjustment. As the iterations increase, the array output gradually converges towards the signal of interest until the adaptive weights reach their optimal values. These results demonstrate the LMS algorithm's ability to accurately track the signal of interest and achieve stable convergence as the learning process progresses.

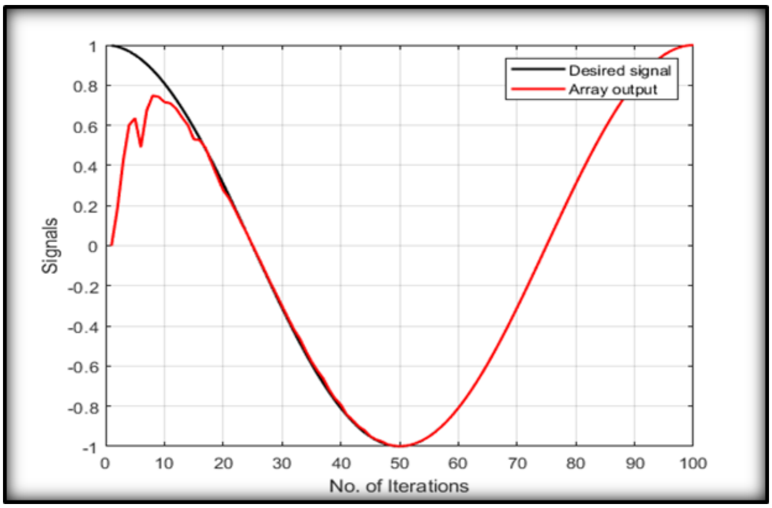

Figure 8. Performance of the signal of interest tracking obtained using the adaptive LMS algorithm

VII. Conclusion

This research paper presented an application and performance evaluation of the adaptive LMS algorithm using a linear uniform array (ULA). Testing is conducted under various scenarios to assess its ability to steer beams, suppress interference, achieve convergence, and optimize adaptive weights until it reaches a stable state and accurately tracks the signal of interest.

The simulation results showed that the algorithm successfully steers the array response towards the signal of interest directions while efficiently suppressing interference signals. Mean squared error (MSE) analysis confirmed rapid convergence with low error. Furthermore, the evolution of the adaptive weights demonstrated stable adaptation throughout the learning process. Signal tracking results also confirmed the beamformer's ability to satisfactorily track the signal of interest after convergence.

Overall, the results demonstrate that the LMS algorithm provides an efficient and reliable solution for adaptive beamforming in wireless communication systems. Due to its low computational complexity and satisfactory convergence performance, it is a suitable option for smart antenna applications in dynamic wireless environments.

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