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Adaptive Beamforming of Linear Array Antenna System Using Particle Swarm Optimization and Genetic Algorithm

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Abstract: One of the key aspects of 5G networks is the implementation of massive MIMO (Multiple Input Multiple Output) technology combined with adaptive beamforming. This study explores the use of a linear array antenna to manage and reduce unwanted signals such as jamming, interference, and noise, while also boosting the signal strength towards the intended user or device. The main challenge lay in optimizing the weights of the antenna elements, which was tackled by employing adaptive algorithms like LCMV (Linearly Constrained Minimum Variance) and RLS (Recursive Least Squares). To simplify the optimization process, two soft computing techniques—Particle Swarm Optimization (PSO) and Genetic Algorithm (GA)—were utilized. The performance of the beamforming weights and radiation patterns was assessed in terms of minimizing unwanted signals and maximizing the desired signal. To check how well the proposed methods work, some commonly used algorithms like MVDR (Minimum Variance Distortionless Response) and LCMV are also applied. The outcomes were compared to those from other algorithms. A Differential Beamforming method is applied to examine how effectively the system can focus the signal in the target direction while minimizing unwanted interference from other directions. Additionally, the fminsearch algorithm, which is a basic local search method, is used to compare how well it can adjust the beamforming weights compared to the more advanced global optimization techniques. The results indicate that PSO and GA produce highly similar performance levels.

Index Terms: Fitness Value, Jamming Angle, Linearly Constrained Minimum Variance (LCMV) Algorithm, Minimum Variance Distortionless Response (MVDR), Algorithm and Steering Vector

1. Introduction

An array antenna system uses multiple antennas that work together to send or receive signals. These antennas are arranged in a specific way to make communication better. The arrangement helps the system focus the signals in certain directions, making them stronger and clearer. This also reduces unwanted signals or interference. Array antennas play a key role in technologies like 5G, Wi-Fi, and GPS by controlling the direction and strength of signals.

One common type of array antenna is called a linear array. In a linear array, antennas are placed in a straight line. Each antenna in the array, known as an "element", works together with the others to create a stronger, more directed signal. These elements are linked to a transmitter or receiver via a system of cables or circuits. This network manages the signal strength (amplitude) and timing (phase) for each antenna. Adjusting these settings allows the system to focus signals in specific directions, a technique called beamforming. Beamforming helps concentrate energy where it's needed, improving communication range and quality.

The distance between antennas in a linear array is very important. If the antennas are spaced too far apart, the system may create extra unwanted beams, called grating lobes, which can interfere with the main signal. To prevent this, antennas are usually placed at half the wavelength of the signal they handle. Proper spacing ensures the signals from all elements are combined to form a strong and focused main beam.

A major advantage of an array antenna system is its ability to steer signals without physically moving the antennas. This process involves electronic beam steering, achieved by adjusting the signal phase at each antenna to direct the beam's path. This makes the system flexible and efficient, as it can adapt to changes in the environment or user movement. This capability is particularly beneficial in mobile networks, where devices and users are in constant motion.

Another key benefit of array antennas is their high gain, which means they can focus energy in a specific direction. High gain results in stronger signals and better communication over longer distances. This is why array antennas are used in places like base stations, satellites, and radar systems. In wireless networks, they improve coverage, minimize signal loss, and allow the system to support more users at the same time. Their ability to focus signals also helps reduce interference from other devices, ensuring more reliable communication.

Array antennas play a critical role in advanced technologies like massive MIMO (Multiple-Input, Multiple-Output), which are integral to modern networks like 5G. Massive MIMO makes use of extensive antenna arrays to both transmit and receive data concurrently from numerous devices, boosting network capacity and enhancing data transfer rates. In a similar vein, array antennas are vital for satellite communication, providing stable and dependable connections between ground stations and satellites.

While array antennas have many advantages, designing and maintaining them can be challenging. Engineers must determine the spacing, alignment, and signal characteristics of each antenna. Even minor errors can cause signal degradation or interference, compromising the system's efficiency. The feed network, which connects the antennas, must also be designed to handle high frequencies while maintaining signal quality. Sophisticated tools and testing devices are frequently employed to guarantee optimal system performance.

Array antenna systems are powerful tools for improving signal strength and efficiency. By focusing signals, steering beams electronically, and offering high gain, they enable faster and more reliable communication.

The gain pattern or beam direction of a single-element antenna (such as Yagi-Uda, spiral, dipole, or horn) can only be modified by adjusting the dimensions of its components or employing mechanical steering. In contrast, array antennas are widely used in wireless networks to attain specific directivity, beam shapes, and steerable beams. The overall radiation pattern is determined by factors such as the relative magnitudes of feed currents, phase differences, spacing between antenna elements, and the geometric layout of the array. Each antenna element's weighting factor is controlled by an adaptive algorithm, which dynamically shapes the antenna beam based on input and desired signal components.

The rest of the paper is organized as: section 2 gives literature review, section 3 provides theoretical analysis of Array Antenna System(AAS) and the corresponding algorithms in a nutshell, section 4 deals with the methodology of the research, section 5 priorities results based on theory and methodology and section 6 concludes the entire analysis.

2. Literature Review

Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) are flexible optimization techniques that have been applied across various fields with significant contributions to advancements in array antenna beamforming. PSO can be designed to maximize desired signal and minimize interference as discussed in [1]. By fine tuning velocity and position, the exploration abilities of PSO can be improved as shown in [2]. To attain the desired beam pattern, the process is carried out iteratively, as emphasized in [3]. According to [4], the main advantage of PSO is its capability to address nonlinear and complex optimization problems, which makes it particularly effective for optimizing antenna arrays.

Besides Genetic Algorithm and Particle Swarm Optimization Algorithm, several other algorithms have been known for their important contributions to enhance beamforming performance. The fminsearch optimization algorithm, derived from the Nelder-Mead simplex method, focuses on identifying the optimal solution by reducing the average total cost [5,6]. Found from [7,8], the differential beamforming technique enhances signal clarity in noisy settings by examining wavefield variations along the main lobe prior to beamforming and is commonly applied in microphone arrays, antenna systems, and acoustic processing. The Linearly Constrained Minimum Variance (LCMV) beamformer calculates the best weights to strengthen signals from a specific direction while reducing noise and interference, based on a steering vector and signal data as explained in [8,9].

In [10], the authors have manipulated Genetic Algorithm to adjust the signal strength of each antenna with the aim of load balancing among all elements. Research combining genetic algorithms with convolution techniques has been carried out and presented in [11] where Conv/GA and D Conv/GA utilize a convolution process to vary the excitation to the elements and a genetic algorithm is used to optimize the spacing of the antenna elements. Genetic Algorithm (GA) was used in [12] to arrange microphone arrays to improve the clarity and accuracy of beamforming, with linear arrays offering the best results in terms of resolution and reliability compared to other setups. Massive MIMO-OFDM combined with a genetic algorithm (GA) used in [13] enhances signal quality by optimizing the Signal-to-Interference-plus-Noise Ratio (SINR), reducing bit error rate (BER), and lowering power consumption, all of which contribute to better service quality. In [14], the dynamic clustering relay node using a genetic algorithm (DCRN-GA) approach proves to be an efficient method for conserving energy in IoT network planning and design, outperforming other methods like the Low Energy Adaptive Clustering Hierarchical (LEACH) routing protocol and the standard Dynamic Clustering Relay Node (DCRN). PSO particularly optimizes the amplitude and position of antenna elements to improve the performance of beamforming and antenna array synthesis as compared by the authors in [15]. In [16], a modified particle swarm optimization (PSO) algorithm is introduced to effectively combine multiple objectives in array beamforming. Low complexity PSO based algorithm is combined with sparse antenna arrays to significantly improve the performance of millimeter-wave(mmWave) Non-Orthogonal Multiple Access(NOMA) as explained in [17].

In [18], a modified PSO algorithm called Culled Fuzzy Adaptive Particle Swarm Optimization (CFAPSO) is shown to outperform other algorithms like Adaptive Particle Swarm Optimization (APSO), Binary Particle Swarm Optimization (BPSO), Genetic Algorithm (GA), Covariance Matrix Adaptation Evolution Strategy (CMA-ES), and), Microstrip Patch Antennas (MPA) in solving both simple and complex problems, making it a great fit for Collaborative Beamforming (CBF) due to its simplicity and low computational demands. In [19],it is shown that the Particle Swarm Optimization (PSO) algorithm, when combined with statistical methods like Support Vector Machine (SVM), Artificial Neural Network (ANN), and Adaptive Neuro-Fuzzy Inference System (ANFIS), as well as evolutionary techniques such as Simulated Annealing (SA), Genetic Algorithm (GA), and Bat Algorithm (BA), proves to be an effective optimization tool, with variations like Enhanced PSO (EMPSO) and Novel PSO (NPSO) offering faster convergence and better efficiency compared to Non-dominated Sorting Genetic Algorithm II (NSGA-II), while other PSO variations such as PSO-GA, Cooperative PSO (CPSO), Multi-Stage PSO (MSPSO), PSO with Differential Evolution (PSO-DE), PSO-SVM, and PSO with Multiple Swarm (PSO-MS) also show quicker convergence than the traditional Genetic Algorithm (GA). A robust beamforming approach combining neural networks and fuzzy logic was proposed in [20], which improves resistance to Direction Of Arrival(DOA) estimation errors and interference, enhancing measurement data fusion systems. Particle Swarm Optimization (PSO) can enhance the radiation patterns of phased arrays by modifying solely the phase of the antenna elements which simplifies the optimization procedure and lowers costs by eliminating the need for intricate hardware modifications to adjust the amplitude, as discussed in [21]. The effectiveness of PSO in beamforming has been shown in [22]. Recent developments include the use of deep reinforcement learning for distributed coordinated beamforming in massive MIMO networks as done in [23], addressing real-time adaptability in dynamic environments with multiple users. In parallel, hybrid optimization techniques—such as combining PSO with Differential Evolution—have been explored to solve constrained beamforming problems more effectively by leveraging feasibility rules in [24]. Recent work also shows deep learning, such as CNN-based beam prediction in 5G massive MIMO systems, can greatly improve accuracy and reduce latency [25]. Meanwhile, PSO remains an efficient alternative for real-time multi-user mmWave NOMA beamforming due to its low complexity and fast convergence [26].

3. Theoretical Analysis

The gain pattern or beam direction of a single-element antenna (such as Yagi-Uda, spiral, dipole, or horn) can only be altered by modifying the dimensions of its components or utilizing mechanical steering. In wireless networks, array antennas are commonly employed to achieve specific directivity, beam shapes, and steerable beams.

The overall radiation pattern is determined by factors such as the relative magnitude of feed currents, phase differences, spacing between antenna elements, and the array's geometric design. An adaptive algorithm controls the weighting factor of each antenna element, using the input and desired signal components to dynamically shape the antenna beam.

In an array antenna, multiple individual antennas are linked together and organized in a specific arrangement (such as linear, planar, or circular) to function as one cohesive unit. The resulting radiation pattern from the array is essentially a composite of the patterns from each individual antenna element. While single antenna elements are widely used, they are generally designed for a fixed feed current and frequency band.

There are five factors that control the overall pattern of an array antenna. They are:

1. The geometrical configuration of the overall array (linear, circular, rectangular, spherical, etc.)
2. The relative displacement between the elements
3. The excitation amplitude of the individual elements
4. The excitation phase of the individual elements
5. The relative pattern of the individual elements

Depending on the relative phase, amplitude, and separation among the antenna elements, we can achieve a beam with the desired directivity and direction.

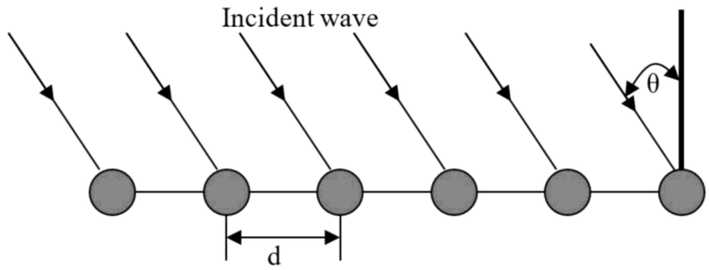


Fig. 1. Linear array antenna

3.1. Adaptive Beamforming

Adaptive beamforming is a dynamic method that allows us to transmit or receive the desired signal by focusing on its direction of arrival. While signals can originate from various directions, the goal is to adjust the antenna to capture the target signal and reject interference from other sources. The central component of an adaptive beamformer is an adaptive filter, which consists of two key components: a digital filter with modifiable coefficients and an adaptive algorithm that fine-tunes these coefficients to optimize the filter's performance.

In this research work, Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) will also be applied to perform the same task.

3.2. Particle Swarm Optimization(PSO) Algorithm

The Particle Swarm Optimization (PSO) algorithm is employed to determine the optimal weight values for the array of antenna, enabling the suppression of jamming signals coming from a particular angle, θ[27,28]. For optimizing beamforming weights in MIMO systems, where simultaneous signal processing is required, PSO has been widely applied. The technique's ability to reduce interference and enhance signal reception is explained in [3]. PSO algorithm can be designed to minimize interference while maximizing the desired signal, as outlined in [1].

In the Particle Swarm Optimization (PSO) method, the position and velocity of each particle is modified according to Eq. (1) and Eq. (2) as outlined in [29]:

$$v_{\{i,k+1\}} = \omega v_{\{i,k\}} + c_1 r_1 \left(p_{\{i,k\}} - x_{\{i,k\}}\right) + c_2 r_2 \left(g_k - x_{\{i,k\}}\right) \quad (1)$$

$$x_{\{i,k+1\}} = x_{\{i,k\}} + v_{\{i,k+1\}} \quad (2)$$

Where $v_{\{i,k\}}$ is the velocity of particle i at iteration k, $x_{\{i,k\}}$ represents the current position (antenna weights) of particle i, $p_{\{i,k\}}$ is the best position found by particle i, g_k is the global best position across the swarm at iteration k, c_1 and c_2 are the cognitive and social coefficients, r_1 and r_2 are random values between 0 and 1, and ω is the inertia weight.

PSO iteratively searches for the optimal weight vector by adjusting the particles to minimize interference and maximize the desired signal as found in [30]. Enhancing the exploration capabilities of PSO, such as refining velocity and position updates, can significantly improve optimization results, as highlighted in [2]. Once the optimal weights are obtained using the objective function, the next step is to evaluate the beamforming gain, which measures the array's response as a function of the angle θ as done in [31]. The gain is updated iteratively to achieve the desired beam pattern, as highlighted in [3]. As noted in [4], PSO's primary strength lies in solving nonlinear and complex optimization problems, making it well-suited for antenna array optimization. The objective function in PSO for beamforming aims to suppress interference while enhancing desired signal gain. By adjusting the weights and gain, the beamforming response closely matches the desired pattern, as explained in [3]. In MATLAB, the particleswarm function operates by minimizing a custom cost function with an initial search range and swarm size provided as arguments.

Array antenna systems are powerful tools for improving signal strength and efficiency. By focusing signals, steering beams electronically, and offering high gain, they enable faster and more reliable communication.

3.3. Genetic Algorithm(GA)

Genetic Algorithm (GA) which is based on concept of natural selection, applied in adaptive beamforming of a linear array antenna systems to differentiate the desired signal from the interferer signals by altering the weight over time in order to enhance the signal-to-noise ratio (SNR), array output, and errors. It minimizes interference at a particular jamming angle, θ by adjusting the weight of an array antenna system. The genetic algorithm's objective is to enhance the array's response to signals by altering the weights in order to improve system performance while reducing interference.

During the genetic algorithm's development process, the collection of individual weights is updated repeatedly as long as the best possible weight fails to be found. A new group of population of weights are chosen randomly for building the subsequent generation [32] by applying the genetic operators like crossover and mutation to individuals already in the population mentioned in [33,34]. Based on the ability of solving problems a fitness value is assigned with each of the individual solutions [35] which is calculated by using the Eq. (3) of fitness function, [34]

$$F(i) = V - \frac{O(i).P}{\sum_{i=1}^{P} O(i)} \tag{3}$$

where, i^{th} individual has an objective function $O(i)$, size of the population is P and V is a large value that ensures the value of the fitness function always remain non-negative.

New populations are selected according to the convergence rate of Genetic Algorithm [33]. Several methods like the roulette-wheel method, tournament method, rank method, boltzmann method and stochastic universal sampling method are used in selection phase. In [36], the roulette-wheel method was used for selection based on fitness.

According to [37], Crossover is used to generate the offspring from the parent chromosomes. Two individual divides their chromosomal string at random point producing head and tail segments [35] and then exchange their head or tails. The two offspring inherit some genes from each parent.

According to [38], mutation is the random modification of an individual's genetic information caused by radioactive radiation or other environmental effects, which is the final component of genetic algorithms.

3.4. Fminsearch Algorithm

Fminsearch algorithm which is based on Nelder-Mead simplex method based optimization algorithm, used in adaptive beamforming to adjust the beamformer's weights for gaining optimal performance. An objective function is used which measures the performance of the beamformer by minimizing the Interference Plus Noise Power (INP), maximizing Signal to Interference Plus Noise Ratio (SINR). At the very beginning, fminsearch need to have an initial guess $\boldsymbol{w_0}$ for weights of beamformer which is typically set randomly. Later the weights are altered to reduce objective function by applying the steps in each of the iterations which are mentioned later. At the end, the optimal weights that are obtained using the objective function, the next step is to evaluate the beamforming gain, which measures the response of the array antenna as a function of the jamming angle θ.

The main objective of Fminsearch is to find the optimal solution by minimizing the average total cost [5,6]. Fminsearch finds minimum value of an unconstrained multi-variable function using a derivative-free method.

For maximizing the array gain for linear array antenna system, we need to determine the solution with minimum objective function value and let the problem be defined as Eq. (4),

$$min\ f(x) \tag{4}$$

The objective function can be represented as $f : R^n -> R$ [39,40] where the dimension is denoted by n.

A simplex consisting the vertices $x_1, x_2, x_3, \ldots\ldots x_{n+1}$ is a geometric object which is the convex hull of n+1 vertices and the dimension is n.

This method builds a succession of simplices iteratively to approximate the optimal location. The vertices of the simplex ${x_j}_{j=1}^{n+1}$ are sorted according to the objective function values $f(x_1) \leq f(x_2) \leq \ldots \leq f(x_{n+1})$ in each iteration. X_1 is considered to most optimal vertex and the worst vertex is x_{n+1}.

In each of the iterations, four possible operations like reflection, expansion, contraction and shrink operations can possibly be executed. A scalar parameter is associated with each of the operations. α is associated with reflection. Similarly, β with expansion, γ with contraction, and δ with shrink operation. $\alpha > 0$, $\beta > 1$, $0 < \gamma < 1$, and $0 < \delta < 1$ are the values of these parameters and the for the standard implementation [40,41] the values are chosen to be, $\alpha = 1$, $\beta = 2$, $\gamma = \frac{1}{2}$ and $\delta = \frac{1}{2}$.

3.5. Differential Beamforming Algorithm

The differential beamforming technique computes spatial derivatives of the wavefield along the main lobe of an array before applying beamforming algorithms [42]. This method, effective in high-noise environments, is used in microphone arrays, adaptive antenna arrays, and acoustic signal processing [7,8]. The goal is to optimize the weights **w** for a uniform circular array (UCA) to achieve maximum directivity at the desired angle θ, while suppressing interference from unwanted directions, such as the jamming angle θ_{jam} as found in [43].

In adaptive beamforming, the steering vector plays a crucial role in dynamically adjusting the array weights to focus the beam towards a desired angle of arrival (AoA), while minimizing interference. In [44], the optimization of the weight vector **w** is formulated in Eq. (5) as:

$$\boldsymbol{w}_{opt} = arg\ \min_{\mathbf{w}}(E\ [|\boldsymbol{S}(\boldsymbol{\theta_0})^H \mathbf{w}\ - 1\ |^2]\ + \lambda \|\mathbf{w}\|^2\ ) \tag{5}$$

where $\mathbf{S}(\theta_0) = [1, e^{-j\theta_0}, e^{-j2\theta_0}, \ldots.\ e^{-j(N-1)\theta_0},]$ is the steering vector for the required angle θ_0, and λ is the regularization parameter[44]. This cost function aims to minimize the mean squared error between the desired beamforming output and the actual response, while also minimizing the weight vector's norm [44].

In [42], the differential beamforming method also uses a similar optimization function, where the steering vector helps process the spatial differences between microphone elements, enhancing the signal reception from the desired direction while reducing interference. The optimization problem is also expressed in Eq. (6) as:

$$\mathbf{w}_{opt} = arg\ \min_{\mathbf{w}}(E\ [|S(\theta_0)^H\mathbf{w} - 1\ |^2] + \lambda\|\mathbf{w}\|^2\ ) \tag{6}$$

This cost function is crucial for improving the signal-to-noise ratio (SNR) by adjusting the weights based on spatial differentiation, and it applies to both antenna arrays and microphone arrays in beamforming systems [42]. The steering vector $S(\theta_0)$ reflects the phase adjustments across the array elements, enabling beamforming in the direction of a specific angle θ_0. The array weights $\mathbf{w}$ are adjusted using methods such as the Nelder–Mead method to minimize interference while ensuring sharp directionality at θ_0, as detailed in [45].The weights $\mathbf{w}$ are determined using the Nelder-Mead algorithm, which is executed via the fminsearch function in MATLAB to minimize the objective function.

This method is applied in various contexts, including differential microphone arrays and adaptive antenna systems [46,47]. The Nelder–Mead method for optimization in adaptive beamforming is also described in [45,47], delivering a computational approach to accurately and efficiently determine the optimal weight vector for the array.

3.6. Linearly Constrained Minimum Variance (LCMV) Algorithm

The optimum weight vector of 'linearly constrained minimum variance' (LCMV) beamformer is denoted by Eq. (7) [8,9],

$$\mathbf{W}_0 = \frac{g^* R^{-1}\mathbf{S}(\theta_0)}{\mathbf{S}^H(\theta_0)R^{-1}\mathbf{S}(\theta_0)} \tag{7}$$

where $\mathbf{S}(\theta_0) = [1 \quad e^{-j\theta_0} \quad e^{-j2\theta_0}\ldots \quad \ldots \quad e^{-j(M-1)\theta_0}]$ known as steering vector, g is the complex-valued gain, θ_0 desired electrical angle related to physical angle of arrival. In MVDR the gain is considered $g = 1$ as the special case along the direction of θ_0 and a constraint of minimum average is applied in Eq. (7), found in [8,48]. The differential beamforming technique first measures the field derivatives along the main lobe of the array then beamforming algorithm is applied, which is widely used in signal processing of microphone array explained in [7,46]. Nelder–Mead method in detection of minima of objective function (it is actually a numerical method) is also applied to find optimum weight vector of adaptive array antenna system. In Matlab 2018 the function *fminsearch* is used with argument of cots function and initial vector. Application of the minima search under Nelder–Mead method is found in [45,47].

3.7. Minimum Variance Distortionless Response (MVDR) Algorithm

Modern adaptations of the MVDR algorithm address practical challenges in beamforming. For example, a dynamically mutated artificial immune system algorithm boosts the null-steering efficiency of the MVDR beamformer, resulting in a significant improvement in the signal-to-interference-plus-noise ratio (SINR) [49]. Boughaba and Chouaib [50] proposed a refined MVDR beamforming technique that optimizes the performance of linear dipole arrays by explicitly addressing mutual coupling effects. Robust designs of MVDR beamforming use optimal steering vector estimation to mitigate sensitivity to errors and finite snapshots, as detailed in [51]. The MVDR algorithm is applied in Electronically Steerable Parasitic Array Radiator (ESPAR) antennas, enabling effective beam steering and interference suppression [52]. In addition, covariance matrix regularization that utilize shrinkage factors improve performance, particularly in situations with low signal-to-noise ratio (SNR), as outlined in [53]. These advancements underscore the versatility of MVDR-based beamformers in communication systems and signal processing.

The Minimum Variance Distortionless Response (MVDR) beamformer, presented in [54], seeks to minimize the array's power consumption while maintaining the integrity of the desired signal. The MVDR weight vector is expressed as [54]

In Eq. (8):

$$\mathbf{W}_{MVDR} = \frac{R^{-1}\mathbf{S}(\theta_0)}{\mathbf{S}^H(\theta_0)R^{-1}\mathbf{S}(\theta_0)} \tag{8}$$

Where R is the covariance matrix of the received signals and $\mathbf{S}(\theta_0)$ is the steering vector pointing to the desired signal direction. More recently, innovations like GPU-accelerated implementations in [55] have made it possible to apply this algorithm in real-time, including in areas like cardiac ultrasound imaging.

4. Methodology

Different types of adaptive algorithms are used in adaptive beamforming, which transmits or receives the desired signal from a particular direction of arrival at the same time rejecting the unwanted signal of a particular direction. The weighting factors of the array antenna system are adjusted by an adaptive digital filter, which operates in the same way as an artificial neural network (ANN) except for the use of an activation function. Appropriate weighting factors of the Array Antenna System (AAS) provide the array gain such that it increases the gain along the direction of arrival and reduces the gain along the direction of jammers or interferences. The basic architecture of AAS with adaptive beamforming technique is shown in Fig. 2.

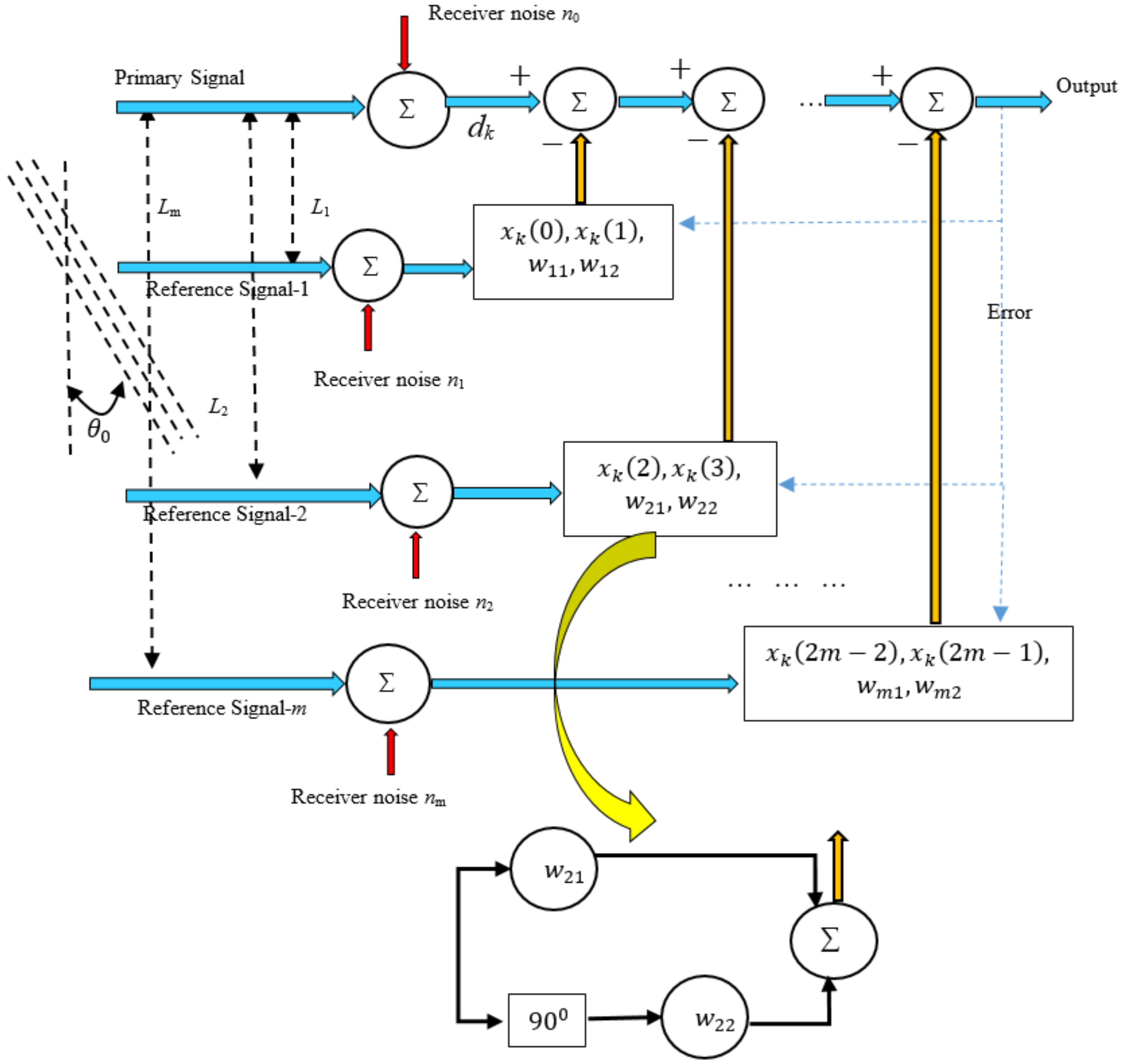


Fig. 2. The basic architecture of adaptive beamforming

If the wave-front makes an angle θ_0 with the vertical axis, then for path difference of $l\, sin\, \theta_0$ the change in phase is $\delta_i = \left(\frac{2\pi}{\lambda}\right) L_i\, sin\, \theta_0$. Let the primary signal is $c\, cos\, k\, \omega_0$ and the ith reference signal is $c\, cos(\, k\omega_0 + \delta_i)$.
$\therefore$ The output signal,

$$O(k, \omega_0, \delta_i, w_{ij}) = cos\, k\, \omega_0 - w_{11}\varphi_{11}(k, \omega_0, \delta_i, w_{ij}) - w_{12}\varphi_{12}(k, \omega_0, \delta_i, w_{ij}) - \cdots \cdots\cdots - w_{m2}\varphi_{m2}(k, \omega_0, \delta_i, w_{ij}) \tag{9}$$

Where,

$$\varphi_{11}(k,\omega_0,\delta_i,w_{ij}) = cos\,k\,\omega_0\,cos\,\delta_1\,\omega_0 - sin\,k\,\omega_0\,sin\,\delta_1\,\omega_0$$
$$\varphi_{12}(k,\omega_0,\delta_i,w_{ij}) = sin\,k\,\omega_0\,cos\,\delta_1\,\omega_0 + cos\,k\,\omega_0\,sin\,\delta_1\,\omega_0$$
$$\varphi_{21}(k,\omega_0,\delta_i,w_{ij}) = cos\,k\,\omega_0\,cos\,\delta_2\,\omega_0 - sin\,k\,\omega_0\,sin\,\delta_2\,\omega_0$$
$$\dots\quad\dots\quad\dots$$
$$\varphi_{m1}(k,\omega_0,\delta_i,w_{ij}) = cos\,k\,\omega_0\,cos\,\delta_m\,\omega_0 - sin\,k\,\omega_0\,sin\,\delta_m\,\omega_0$$
$$\varphi_{m2}(k,\omega_0,\delta_i,w_{ij}) = sin\,k\,\omega_0\,cos\,\delta_m\,\omega_0 + cos\,k\,\omega_0\,sin\,\delta_m\,\omega_0$$

Simplifying,

$$O(k,\omega_0,\delta_i,w_{ij}) = A\,cos(\,k\omega_0-\alpha) = cos\,k\,\omega_0(1 - w_{11}\,cos\,\delta_1\,\omega_0 - w_{12}\,sin\,\delta_1\,\omega_0 - w_{21}\,cos\,\delta_2\,\omega_0 - w_{22}\,sin\,\delta_2\,\omega_0 - \cdots w_{m2}\,sin\,\delta_m\,\omega_0) + sin\,k\,\omega_0(w_{11}\,sin\,\delta_1\,\omega_0 - w_{12}\,cos\,\delta_1\,\omega_0 + w_{21}\,sin\,\delta_2\,\omega_0 - w_{22}\,cos\,\delta_2\,\omega_0 - \cdots\ w_{m2}\,cos\,\delta_m\,\omega_0)\ = cos\,k\,\omega_0 A\,cos\,\alpha + sin\,k\,\omega_0 A\sin\alpha \tag{10}$$

∴ The array gain,

$$A^2 = (1 - w_{11}\,cos\,\delta_1\,\omega_0 - w_{12}\,sin\,\delta_1\,\omega_0 - w_{21}\,cos\,\delta_2\,\omega_0 - w_{22}\,sin\,\delta_2\,\omega_0 - \cdots\ w_{m2}\,sin\,\delta_m\,\omega_0)^2 + (w_{11}\,sin\,\delta_1\,\omega_0 - w_{12}\,cos\,\delta_1\,\omega_0 + w_{21}\,sin\,\delta_2\,\omega_0 - w_{22}\,cos\,\delta_2\,\omega_0 - \cdots w_{m2}\,cos\,\delta_m\,\omega_0)^2 \tag{11}$$

Array gain in generalized form:

$$A(\theta) = \sqrt{\left[1 - \sum_{i=1}^{m}\left[w_{i,1}\cdot\omega_0.\,cos\,\delta_i + W_{i,2}\cdot\omega_0.\,sin\,\delta_i\right]\right]^2 + \left[\sum_{i=0}^{m}\left[\left[w_{i,1}\cdot\omega_0.\,sin\,\delta_i + W_{i,2}\cdot\omega_0.\,cos\,\delta_i\right]\right]\right]^2} \tag{12}$$

The aim of the research work is to optimize the Eq. (12) using different adaptive beamforming algorithms and MLs.

In this paper, the original formulation of the array gain, *A(θ)*, was derived under the assumption of a uniform linear array with fixed antenna spacing of $d=\lambda/2$ and a fixed number of elements. However, real-world implementations often require two-dimensional (2D) or planar array configurations to operate effectively in dynamic environmental conditions (Fig. 3).

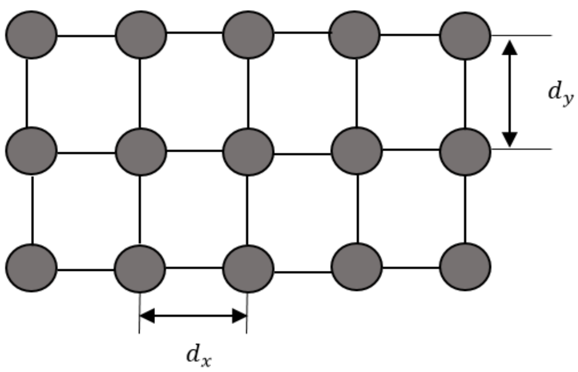


Fig. 3. Two dimensional array environment

To address this, the array gain model has been extended to consider both the x and y axes, enabling more general and realistic antenna geometries. The array gain along the x $axis$ can be expressed as:

$$A_x(\theta) = f(d_x, \mathbf{w}_{ix}, \delta_i, \theta) \tag{13}$$

Where
A_x – array gain along the x $axis$
d_x –spacing between antenna elements along x $axis$
$\mathbf{w}_{ix}$ – weighting coefficient for the *i-th* element in the *x axis*
δ_i – inter element phase shift`
θ – desired angle of arrival
Similarly, the array gain along the y $axis$ is given by:

$$A_y\,(\theta) = f\left(d_y, \mathbf{w}_{iy}, \delta_i, \theta\right) \tag{14}$$

Where
A_y – array gain along the $y\ axis$
d_y –spacing between antenna elements along $y\ axis$
w_{iy} − weighting coefficient for the *i-th* element in the *y axis*
The overall array gain for a 2D planar array is obtained as the product of the gains along each axis:

$$A(\theta) = A_x(\theta)\ .\ A_y(\theta) \quad (15)$$

This non-linear equation captures the interaction between spatial dimensions, providing a more accurate representation of beamforming behavior in 2D arrays, which can be effectively optimized using Particle Swarm Optimization (PSO) and Genetic Algorithms (GA). This approach can also extend to circular arrays with radially arranged elements for practical beamforming. However, since the two evolutionary algorithms are inherently slow, making it suitable for linear array antenna configuration for our paper, further extension of the array gain to two dimensions will be explored in future work on advanced geometries and optimization under real-world constraints.

Beamforming is sensitive to parameter variations. This work used fixed antenna spacing (d = λ/2) for ideal performance, but practical spacing varies, affecting array geometry, beam shape, and SNR. Such variations can cause side lobes or beam distortion. Future work will model these effects with adaptive weighting to maintain performance.

This paper used metrics like radiation patterns and array factors but did not evaluate system-level indicators such as SINR, SNR, or BER due to the absence of signal power, interference, and noise modeling. Future work will include these for SINR-based optimization and BER analysis under real conditions.

Lastly, user mobility and changing environments cause dynamic angles, interference, and SNR variations. These were not addressed here but are crucial for realistic beamforming. Future research will develop real-time adaptive methods to handle mobility and environmental changes for robust performance

4.1. Particle Swarm Optimization (PSO) Algorithm

Our proposed algorithm for Particle Swarm Optimization (PSO) is:

Algorithm 1: Particle Swarm Optimization (PSO) Algorithm

Input: Desired angle of arrival, relative path delays, angular frequency lower bounds and upper bounds for optimization variables, number of optimization variables.
Output: Optimal beamforming weights
Procedure:
Start
1) Define constants:
$\boldsymbol{\theta} \leftarrow \pi/6$, $L_1 \leftarrow \pi/2$, $L_2 \leftarrow \pi/4$, $\boldsymbol{\omega_0} \leftarrow 1$, **LB** ← [−2, −2, −2, −2], **UB** ← [2, 2, 2, 2], *nvars* ←4
2) Define the objective function $\boldsymbol{f(x)}$ as follows:

$$f(x) = \sqrt{[1 - x_1\ \cos(a) - x_2\ \sin(a) - x_3\ \cos(b) - x_4\ \sin(b)]^2 + [x_1\ \sin(a) - x_2\ \cos(a) - x_3 \sin(b) - x_4\ \cos(b)]^2}$$

where $a = L_1 * \sin(\theta) * \omega_0$ and $b = L_2 * \sin(\theta) * \omega_0$
3) Use the Particle Swarm Optimization (PSO) algorithm to find the optimal vector that minimizes *f*(*x*):
x_optimal ← *particleswarm*(*f*, *nvars*, **LB**, **UB**)
4) Return x**_optimal**
End

Where,
θ – desired angle of arrival (set to $\pi/6$)
L_1 – relative path delay for antenna element 1 (set to $\pi/2$)
L_2 – relative path delay for antenna element 2 (set to π/4)
ω_0 − normalized angular frequency (set to 1)
LB − lower bounds for optimization variables = [-2, -2, -2, -2]
UB − upper bounds for optimization variables = [2, 2, 2, 2]
nvars − number of optimization variables (set to 4)
x_optimal − optimal beamforming weight components

4.2. Genetic Algorithm (GA)

Our proposed algorithm for Genetic Algorithm(GA) is as:

Algorithm 2: Genetic Algorithm (GA)

Input: Desired angle of arrival, relative path delays, angular frequency, initial guess of beamforming weight components,
lower bounds and upper bounds for optimization variables, number of optimization variables

Output: Optimal beamforming weights, value of the objective function at optimal beamforming weights

Procedure:

Start

1) Define constants:

$\boldsymbol{\theta} \leftarrow \pi/6$, $L_1 \leftarrow \pi/2$, $L_2 \leftarrow \pi/4$, $\boldsymbol{\omega_0} \leftarrow 1$

2) Define the objective function $\boldsymbol{f}(\boldsymbol{x})$ as follows:

$$f(x) = \sqrt{[1 - x_1\,\cos(a) - x_2\,\sin(a) - x_3\,\cos(b) - x_4\,\sin(b)]^2 + [x_1\,\sin(a) - x_2\,\cos(a) - x_3\sin(b) - x_4\,\cos(b)]^2}$$

where $a = L_1 * \sin(\theta) * \omega_0$ and $b = L_2 * \sin(\theta) * \omega_0$

3) Initialize parameters:

$\mathbf{x_0} \leftarrow [1,1,1,1]$, **LB** $\leftarrow [-2, -2, -2, -2]$, **UB** $\leftarrow [2, 2, 2, 2]$, *numberOfVariables* $\leftarrow 4$

4) Create optimization options:

options ⟵ *optimoptions*(*'fmincon', 'Display', 'iter', 'Algorithm', 'sqp'*)

5) Create optimization options 'opts' for genetic algorithm:

opts ⟵ *optimoptions*(*@ga, 'PlotFcn', @gaplotbestf, @gaplotstopping*)

6) Call genetic algorithm based optimization function:

[*x, Fval, exitFlag, Output*] ⟵ *ga*(*f, numberOfVariables, [], [], [], [], [], [], [], opts*)

7) Call the constrained nonlinear optimization function:

[$\mathbf{X}_{optimal}$, $F_{optimal}$] ⟵ *fmincon*(*f*, x_0, *[], [], [], []*, **LB**, **UB**, *[], options*)

8) Return [$\mathbf{X}_{optimal}$, $F_{optimal}$]

End

Where

θ – desired angle of arrival (set to $\pi/6$)

L_1 – relative path delay for antenna element 1 (set to $\pi/2$)

L_2 – relative path delay for antenna element 2 (set to $\pi/4$)

ω_0 − normalized angular frequency (set to 1)

$\mathbf{x_0}$ − initial guess of beamforming weight components = [1, 1, 1, 1]

LB − lower bounds for optimization variables = [-2, -2, -2, -2]

UB − upper bounds for optimization variables = [2, 2, 2, 2]

numberOfVariables− number of optimization variables (set to 4)

$\mathbf{X}_{optimal}$ − optimal beamforming weight components

$F_{optimal}$ − value of the objective function at optimal beamforming weights

4.3. Fminsearch Algorithm

Fminsearch Algorithm for two elements is:

Algorithm 3: Fminsearch Algorithm

Input: Desired angle of arrival, relative path delays, angular frequency, initial guess of beamforming weight components.

Output: Optimal beamforming weights, value of the objective function at optimal beamforming weights, exit flag, additional output information

Procedure:

Start

1) Define constants:

$\theta \leftarrow \pi/6$, $\lambda \leftarrow 1$, $L_1 \leftarrow \pi/2$, $L_2 \leftarrow \pi/4$, $\boldsymbol{\omega_0} \leftarrow 1$

2) Define the objective function $\boldsymbol{f}(\boldsymbol{x})$ as follows:

$$f(x) = \sqrt{[1 - x_1\,\cos(a) - x_2\,\sin(a) - x_3\,\cos(b) - x_4\,\sin(b)]^2 + [x_1\,\sin(a) - x_2\,\cos(a) - x_3\sin(b) - x_4\,\cos(b)]^2}$$

where $a = L_1 * \sin(\theta) * \omega_0$ and $b = L_2 * \sin(\theta) * \omega_0$

3) Create optimization options structure named options for find mean search algorithm and set parameter 'PlotFcns' and specify plotting function optimplotfval:

options ⟵ *optimset('PlotFcns', @optimplotfval)*

4) Call the find mean search algorithm function:

x ⟵ *fminsearch(f,* **v***, options)*

5) Create optimization options structure named 'options':

options ⟵ *optimset('Display', 'iter', 'PlotFcns',@optimplotfval)*

6) Call the find mean search algorithm function 'fminsearch':

[**x**, *fval*, *exitflag*, *output*] ⟵ *fminsearch(f,* **v**, *options)*

7) Return [**x**, *fval*, *exitflag***,** *output*]

End

Where

θ – desired angle of arrival (set to $\pi/6$)

λ – wavelength of the carrier frequency (set to 1 unit)

L_1 – relative path delay for antenna element 1 (set to $\lambda/4$)

L_2 – relative path delay for antenna element 2 (set to $\lambda/2$)

ω_0 − normalized angular frequency (set to 1)

v − initial guess of beamforming weight components = [−0.6, −1.2, 0.135, 1]

x − optimal beamforming weight components

fval − value of the objective function at optimal beamforming weights

exitflag − an integer flag indicating the reason why the algorithm is terminated

output − structure with additional information like iterations, function count, algorithm, message

4.4. Differential Beamforming Algorithm

Differential Beamforming Algorithm is:

Algorithm 4: Differential Beamforming Algorithm

Input: Number of elements, speed of light, carrier frequency, array radius of Uniform Circular Array(UCA), jamming angle, steering angle, array geometry

Output: Beam pattern

Procedure:

Start

1) Define constants:

$N \leftarrow 4$, $c \leftarrow 343$, $f_c \leftarrow 4000$

2) Compute wavelength λ:

$\lambda \leftarrow \frac{c}{f_c}$

3) Define array radius r:

$r \leftarrow 0.1 \cdot \lambda$

4) Define jamming angle *'jam'*:

jam ← 30

5) Define angular points for evaluation:

angpoints ← -180:1:180

6) Compute differential beamforming weights and array geometry:

[**w**, *pos*] ← *diffbfweights* (*N*, *r*/λ, *jam*, *SteerAngle* = -90, *ArrayGeometry* = *'UCA'*)

7) Calculate beam pattern:

b_p ← *arrayfactor* (*pos*, *angp*, *w*)

8) Plot beam pattern using polar coordinates:

polarpattern (*angp*, *mag2db*(*abs*(b_p)), *NormalizeData = true, MagnitudeLimMode = manual, MagnitudeLim* = [-50,0])

9) Return b_p

End

Where

N – number of array elements

c – speed of light

f_c – carrier frequency

r – radius

jam − jamming angle

$SteerAngle$ − steering angle
$ArrayGeometry$ − Array Geometry
b_p − beam pattern

4.5. Linearly Constrained Mean Variance (LCMV) Algorithm

Linearly Constrained Mean Variance (LCMV) Algorithm is:

Algorithm 5: Linearly Constrained Mean Variance (LCMV) Algorithm

Input: Carrier frequency, array configuration, test signal, angle or arrival, jammer angle, noise

Output: Beamformed output signal
Procedure:
Start

1) Set wavelength $\lambda \leftarrow \frac{c}{f_c}$ where c is the speed of light
2) Initialize Uniform Linear Array: $A \leftarrow$ ULA with 4 elements spaced at $\frac{\lambda}{2}$
3) Generate test signal s(t) of length 300 with active samples from indices 201 to 205 set to 1
4) Collect received signal $x \leftarrow \text{collectPlaneWave}(A, s(t), \theta_{sig}, f_c)$
5) Generate jammer signal $j \leftarrow \text{BarrageJammer}(ERP, 4, SamplesPerFrame, 300)$
6) Collect jammer received signal $j_{sig} \leftarrow \text{collectPlaneWave}(A, j, \theta_{jam}, f_c)$
7) Add complex Gaussian noise $j_{sig} \leftarrow j_{sig} + n$
8) Form received signal $r \leftarrow x + j_{sig}$
9) Compute Steering Vector **a** $\leftarrow SteeringVector(A, \theta_{sig}, f_c)$
10) Initialize LCMV Beamformer with constraint **a**
11) Compute output and weights $[y_{LCMV}, \mathbf{w_{LCMV}}] \leftarrow \text{LCMVbeamformer}(r, j_{sig})$
12) Return y_{LCMV}
End

Where
f_c – carrier frequency
c – speed of light
A – array configuration
$s(t)$ – test signal
θ_{sig} – angle of arrival
θ_{jam} – jammer angle
n − noise (computed as $\sqrt{noisePwr/2}.(randn + j.randn)$)
y_{LCMV} – Beamformed output signal
j_{sig} − jammer received signal
x – received signal
r – formed received signal

4.6. Minimum Variance Distortion Response (MVDR) Algorithm

Minimum Variance Distortion Response (MVDR) Algorithm is:

Algorithm 6: Minimum Variance Distortion Response (MVDR) Algorithm

Input: Number of elements, element spacing, jamming angles, signal angles, jammer power
Output: Beam formed weights
Procedure:
Start

1) Define constants $\mathbf{elementPos} \leftarrow (\mathbf{0}{:}\,\boldsymbol{N-1}).\boldsymbol{d}$
2) Compute element positions: $\mathbf{elementPos} \leftarrow (\mathbf{0}{:}\,\boldsymbol{N-1}).\boldsymbol{d}$
3) Define $\mathbf{jammingAngles} \leftarrow [\mathbf{30}, \mathbf{150}], \mathbf{jammerPower} \leftarrow \mathbf{db2pow}(\mathbf{-10})$
4) Compute $\boldsymbol{S_n} \leftarrow \mathbf{sensorcov}(\mathbf{elementPos}, \mathbf{jammingAngles}, \mathbf{jammerPower})$

5) Define signal arrival angles, $\mathbf{signalAngles} \leftarrow [-\mathbf{90}, \mathbf{90}]$
6) Compute MVDR weights: $\mathbf{w} \leftarrow \mathbf{mvdrweights}(\mathbf{elementPos}, \mathbf{signalAngles}, \boldsymbol{S_n})$
7) Define plotting angles: $\mathbf{plotangle} \leftarrow -\mathbf{180}: \mathbf{1}: \mathbf{180}$
8) Compute steering vector: $\mathbf{vv} \leftarrow \mathbf{steervec}(\mathbf{elementPos}, \mathbf{plotangle})$
9) Return **y**
End

Where
N – number of array elements
d – Spacing between array elements
jammingAngles – jamming angles
signalAngles – signal angles
S_n – sensor covariance matrix
w – MVDR weights
vv – steering vector
y – beamformed weights

5. Results and Discussions

The search space of vector of weighting factor of Array Antenna System (AAS) is very wide and has a huge number of possible solutions for particular direction of arrival of signal, at the same time for the arrival of jammer along a particular direction. Any local solution can provide the appropriate directivity and radiation pattern of the array.

5.1. Particle Swarm Optimization(PSO) Algorithm

We applied Particle Swarm Optimization (PSO) on the expression of array gain for a four-element and eight-element linear array antenna, and the corresponding result is shown in Fig. 4. When angle of arrival of signal, $\theta_s = -90^{\circ}$ and arrival of jammer, $\theta_j = 30^{\circ}$,the weight vectors are found as: for the four-elements array, $\mathrm{w} = [-1.6237, 1.2930, 1.9292, -1.4332]$, and for the eight-elements array, $\mathrm{w} = [-0.5507, 1.9350, 1.9993, -1.8196, -0.5707, 0.5277, -0.7072, -0.1089]$.

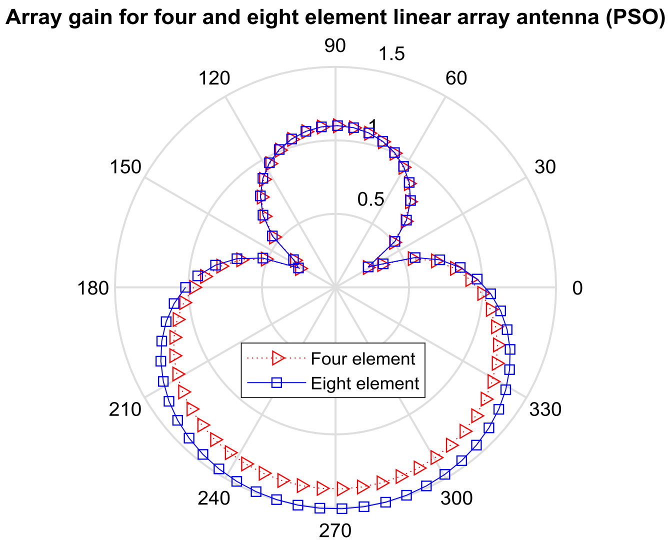
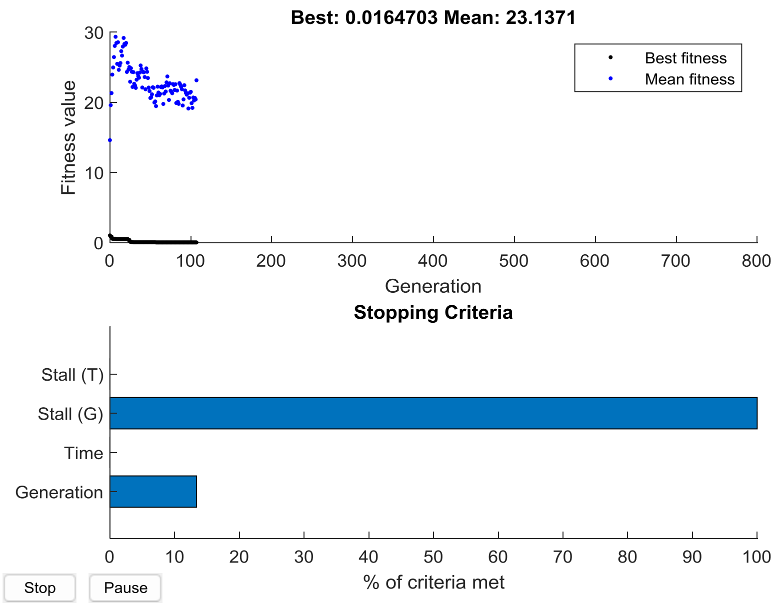


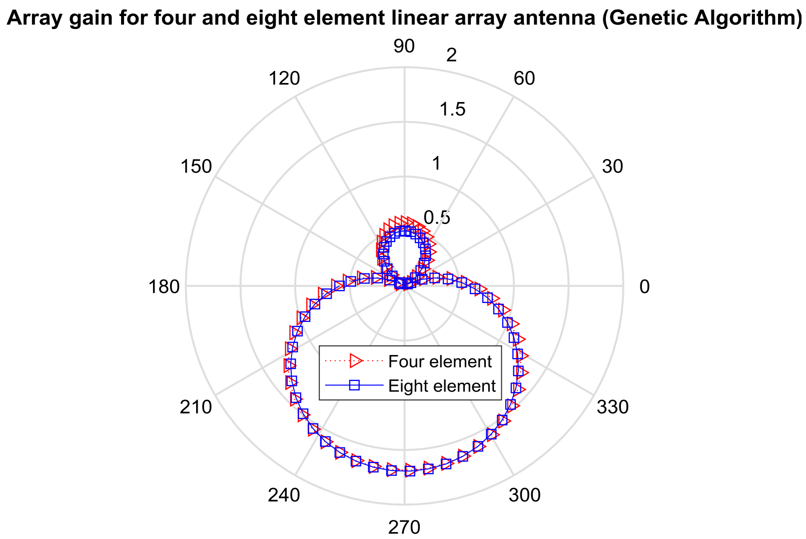
Fig. 4. The results of PSO when $\theta_s = -90^{\circ}$ and $\theta_j = 30^{\circ}$ for four and eight elements linear array antenna

5.2. Genetic Algorithm (GA)

Next, we apply GA in determining directivity pattern of the same AAS. The variation of fitness value until fulfillment of requirement of termination criteria and the resultant directivity pattern are shown in Fig. 5 for the $\theta_s = -90^0$ and $\theta_j = 30^0$. The weighting vector derived from optimization of the array gain is, $\mathrm{w} = [0.5825, 0.2008, 0.3088, 0.4201]$ and $\mathrm{w} = [0.6231, -0.0482, 0.2283, 0.1293, 0.1325, 0.2246, 0.0934, 0.2836]$ for four elements and eight elements array respectively.



(a)

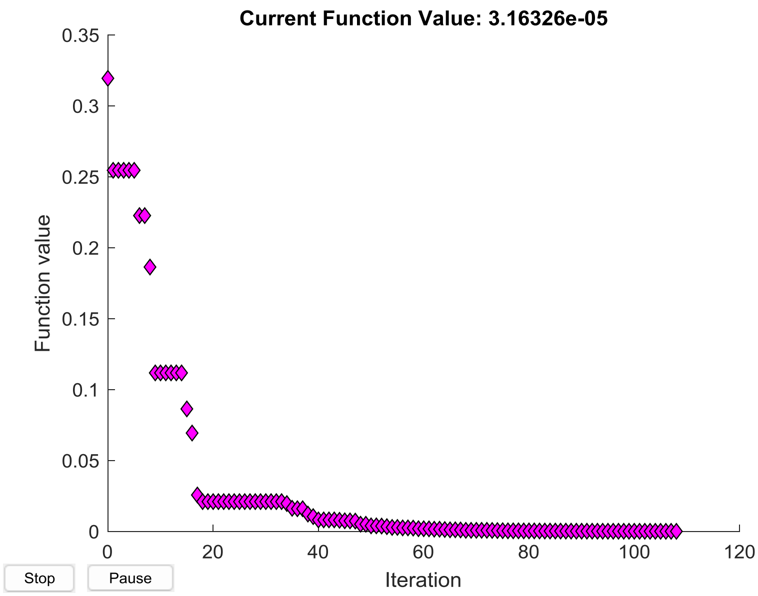


(b)

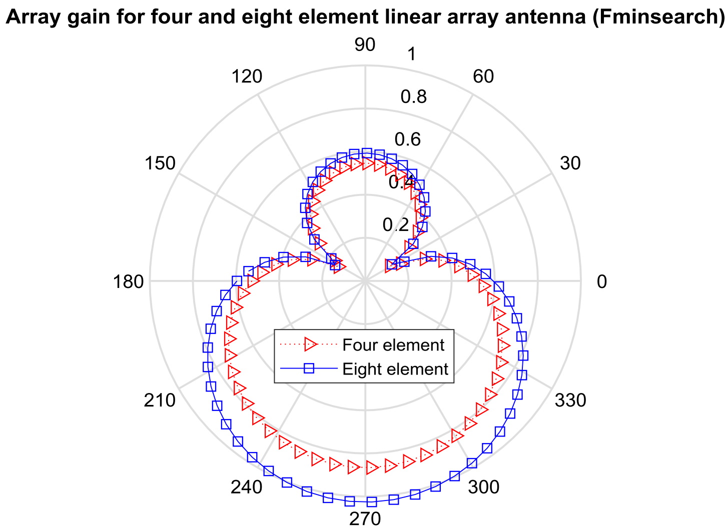
Fig. 5. (a). Variation of fitness value of GA (b). Profile of four and eight elements linear array gain of GA when $\theta_s = -90^{\circ}$ and $\theta_j = 30^{\circ}$

5.3. *Fminsearch Algorithm*

The *fminsearch* algorithm is used to find the minima of nonlinear equation using arbitrary starting point. First of all, this algorithm is applied on array gain equation since it can provide local minima with low complexity. The convergence towards the minima with each iteration and the corresponding radiation pattern on azimuth plane is shown in Fig. 6 taking the number of antenna elements, $N = 4$ and $N = 8$, arrival of signal along -90^0 and arrival jammer along 30^0. The weight vector of the linear array is found: $w = [0.5561 \quad -1.5633 \quad 0.2223 \quad 1.7292]$ for four element array and $w = [-0.5264 \quad -1.2042 \quad 0.1397 \quad 0.9675 \quad -0.2257 \quad 0.1392 \quad 1.5257 \quad 0.4414]$ for eight elements array.



(a)



(b)

Fig. 6. (a). Convergence to minima with each iteration (b). Profile of four and eight elements linear array gain of Fminsearch Algorithm when $\theta_s = -90^\circ$ and $\theta_j = 30^\circ$

5.4. Differential Beamforming Algorithm

The result of differential beamforming algorithm applied to a uniform linear array (ULA) of four and eight elements is shown in Fig. 7.The weight vectors are found as: $w = [0.1800 + 0.0000i, 0.0103 - 0.5302i, 0.1800 + 0.0000i, 0.0103 + 0.5302i]$ and $w = [0.0899 + 0.0000i, 0.0457 - 0.1926i, 0.0030 - 0.2714i, 0.0457 - 0.1926i, 0.0899 + 0.0000i, 0.0457 + 0.1926i, 0.0030 + 0.2714i, 0.0457 + 0.1926i]$ for four and eight elements array respectively when $\theta_s = -90^0$ and $\theta_j = 30^0$.

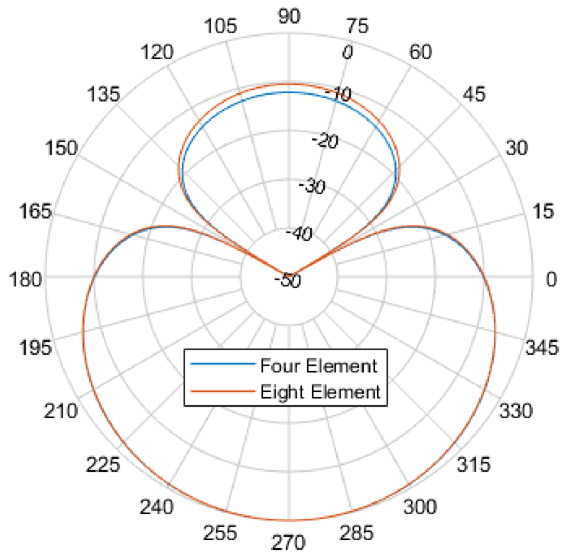


Fig. 7. The results of differential beamforming for $\theta_s = -90^{\circ}$ and $\theta_j = 30^{\circ}$

5.5. Linearly Constrained Minimum Variance (LCMV) Algorithm

Next, we applied the convectional adaptive beamforming algorithm: LCMV to a uniform linear array (ULA) of four elements and eight elements and the result is shown in Fig. 8. The weight vectors are respectively found as: $w = [0.0173 - 0.2542i, 0.0124 + 0.2365i, 0.0031 - 0.2586i, 0.0080 + 0.2507i]$ and $w = [-0.0802 - 0.1533i, -0.0766 + 0.1805i, -0.0088 - 0.0995i, -0.0049 + 0.0976i, 0.0045 - 0.1348i, -0.0109 + 0.0978i, -0.0126 - 0.1106i, -0.0047 + 0.1261i]$ for $\theta_s = -90^0$ and $\theta_j = 30^0$.

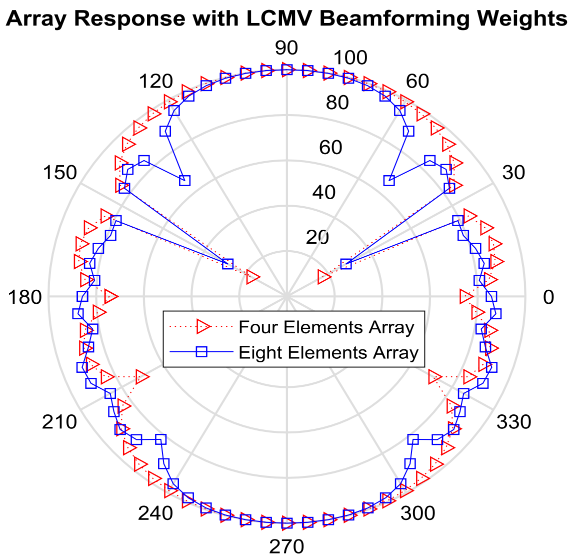


Fig. 8. The results LCMV for $\theta_s = -90^{\circ}$ and $\theta_j = 30^{\circ}$

5.6. Minimum Variance Distortion Response (MVDR) Algorithm

Similarly, we applied another convectional adaptive beamforming algorithm: MVDR to a uniform linear array (ULA) of four elements and eight elements and the result is shown in Fig. 9. The weight vectors for four elements and eight elements are respectively found as: $w = 0.2500 + 0.0000i, -0.2500 + 0.0000i, 0.2500 + 0.0000i, -0.2500 - 0.0000i]$ and $w = 0.1250 + 0.0000i, -0.1250 + 0.0000i, 0.1250 + 0.0000i, -0.1250 - 0.0000i, 0.1250 + 0.0000i, -0.1250 - 0.0000i, 0.1250 + 0.0000i, -0.1250 - 0.0000i]$ for $\theta_s = -90^0$ and $\theta_j = 30^0$.

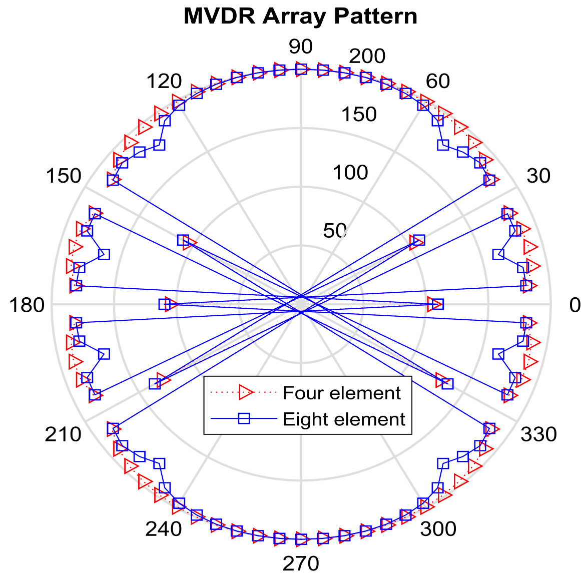


Fig. 9. The results MVDR for $\theta_s = -90^\circ$ and $\theta_j = 30^\circ$

6. Conclusion

In order to minimize interference and maximize signal transmission or reception from a certain direction using an array antenna system, adaptive beamforming uses a variety of techniques. This is accomplished by varying the array antenna system's weighting parameters. These weights determine the array's gain, which maximizes the direction of the desired signal while reducing interference. In order to enhance performance, the thesis focused on optimizing the generalized array gain equation using adaptive algorithms and Machine Learning approaches. In this thesis work, Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) were applied to perform the same task. The weighting factors and radiation pattern for different directions of cancellation of unwanted signals and direction desired signals are shown and compared with existing adaptive algorithms like MVDR, LCMV and found much closed results.

In the future, other methods like Ant Colony Optimization, Artificial Bee Colony, or hybrid techniques that use both local and global search can be tried to improve the performance and accuracy of adaptive beamforming. These approaches may help in finding better solutions faster and could be more effective in handling complex signal environments or real-time applications.

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