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Optimizing Planar Antenna Arrays Using Genetic Algorithms for Enhanced Radar Performance in Direction of Arrival Estimation

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Abstract

This paper proposes the optimization of planar antenna arrays for DOA estimation enhancement in radar systems, where accuracy and computational efficiency need to be well balanced. This work describes a new methodology using GAs to obtain an optimal configuration of the antenna elements, allowing a considerable reduction in computational complexity. Using the ESPRIT algorithm for azimuth and elevation angle estimation, the proposed approach achieves an RMSE as low as 0.2 degrees under an SNR of 20 dB. For practical setups, an antenna size configuration of M = 8, N = 3 with 85 snapshots can achieve an optimal tradeoff, reducing the computational cost by 35% compared to conventional methods while maintaining high accuracy. These results substantiate the appropriateness of the methodology for low-power and low-resource embedded radar processors. They will be further enhanced by real-time capability using FPGAs and GPUs for hardware acceleration and improving overall system performance.

Keywords: Antenna; Direction of arrival; Genetic algorithm; Planar array

1. Introduction

DOA "Direction of arrival" is a metric in single processing to determine the angle from which a signal or wave originates. This leads to its use in satellite communication systems, such as radars, wireless communications, military domains, etc [1], [2]. This usage requires an accurate DOA, hence planar antenna arrays will be used, as they allow the DOA to give the foremost measures. Planar antenna arrays (i.e., uniform rectangular arrays (URA)) have been widely used in many communication fields, such as mobile networks, sonar, navigation, and radar. [3]-[5] is an important technique in estimating the observed signal's Two-dimensional direction of arrival (2D-DOA). Planar antenna arrays perform better than a single sensor in signal reception and parameter estimation. Consequently, many methods have recently been used to estimate the DOA based on the planar array. Multiple signal classification(MUSIC) methods were the first high-resolution to correctly exploit the underlying data model of narrowband signals in additive noise [6], the maximum likelihood method [7], the parallel factor (PARAFAC) method [8], the matrix pencil method [9], the estimation of signal parameters via exploits sensor array rotational invariance. Techniques (ESPRIT) algorithm [10] and so on. Even so, those methods are approached with the problem of high computational complexity in the planar array resolution. The number of sensors in a planar array is an important factor that impacts the performance of DOA estimation methods. More sensors mainly lead to high accuracy in estimating the signal parameters. Although increased hardware costs. Moreover, processing data complexity. Thus, finding the best number of sensors for a specific application seeks to assess factors like desired performance, cost constraints, and computational limitations [11]. However, the determined number of antenna arrays is a highly nonlinear optimization problem. As the complexity of antenna arrays increases, traditional methodologies have arisen as valuable tools for achieving optimal design solutions [12]. Whereas various optimization approaches have different levels of complexity and speed, the outcome in array design depends on their ability to find the best solution [13]. This project used a genetic algorithm (GA), which is like an innovative evolutionary optimization algorithm that explores a wide range of possibilities and has the potential to produce strong and adaptable designs [14]-[16]. This paper investigates the use of planar antenna arrays in radar systems for estimating the DOA of the observed signals, targeting both azimuth and elevation angles. While using algorithms such as ESPRIT to estimate

DOA, previous works usually do not consider the complicated tradeoff between accuracy, computational efficiency, and cost. In this paper, the Algorithm used is ESPRIT; however, a new optimization technique based on GAs was proposed to find the most appropriate number of antenna elements in a planar array, which is a factor that influences the accuracy and efficiency of the radar directly. Unlike the conventional methods, which require fixed or heuristic configurations, the proposed optimization driven by GA can offer a flexible and adaptive solution for enhancing DOA estimation with potentially reduced system complexity and cost. This is considered algorithmic innovation combined with practical efficiency, setting this approach apart from earlier studies.

The paper is organized as follows: Section 2 discusses the research background and previous related works. Section 3 presents a detailed description of the proposed method. Section 4 presents the simulation and results; Section 5 presents the conclusions drawn from this study and recommends possible future research directions.

2. Background and Related Work

2.1 Direction of Arrival Concepts

The DOA estimation aims to determine the direction of arrivals using an antenna array system by processing the received signal that radiates a desired signal while suppressing undesired ones. It determines the angle between the direction of a radio wave's arrival and an array system's axis. This estimate is based on the phase differences measured between multiple arrivals of the received signal at multiple array elements, resulting from differences in travel path. The direction of incoming signals can be inferred by accurately estimating phase differences.

As illustrated in Fig. 1 [17], where the time delay is given according to (1):

$$\tau = \frac{d \sin \theta}{\mathrm{c}} \qquad (1)$$

Where d is the distance between two elements, c is the velocity of light, and θ is the angle of the incoming signal.

2.2 Planar Array and Data Model

As shown in Fig.2 and Fig.3, we consider a uniform rectangular array with M rows and N columns, where M and N represent the number of sensors along the x and y axes, respectively. The distance between adjacent elements is d. In the far field, we assume that they are K uncorrelated sources. The kth source is characterized by its elevation angle (θ_k) and azimuth angle (φ_k).

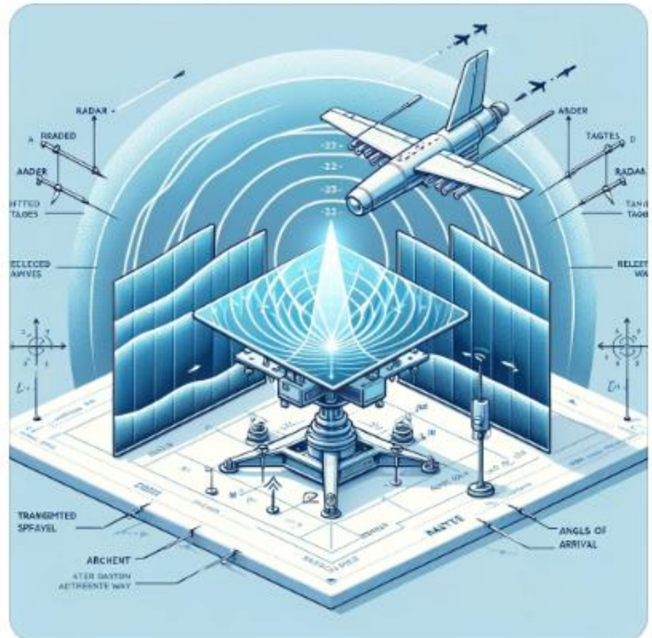


Figure 1. Direction of Arrival Estimation

The principle of the product of array coefficients is used to find the plane antenna array's coefficient. As a result, the quantitative matrix coefficient is given according to (2), (3), and (4) [17]:

$$\mathrm{A}F(\theta,\varphi) = \mathrm{AF}_x.\mathrm{AF}_y = \left[\frac{\sin\left(\frac{M}{2}\right)\Psi_x}{sin\frac{\Psi_x}{2}}\right]\cdot\left[\frac{\sin\left(\frac{N}{2}\right)\Psi_y}{sin\frac{\Psi_y}{2}}\right] \qquad (2)$$

$$\Psi_x = Kd_x sin\theta cos\varphi \qquad (3)$$

$$\Psi_y = Kd_y sin\theta sin\varphi \qquad (4)$$

Equation (2) is derived using the principle of the product of array coefficients for a rectangular planar antenna array. The total array factor $\boldsymbol{AF(\theta,\varphi)}$) is expressed as the product of the array factors along the x- and y-axes, denoted by $\boldsymbol{AF_x}$ and $\boldsymbol{AF_y}$, respectively. These array factors are derived by summing the contributions of all antenna elements, each contributing a phase shift based on its position relative to the origin and the direction of the incident signal.

The phase differences $\Psi_x and \Psi_y$ for the $x\ and\ y$ directions are given by (3) and (4), respectively, where $K = 2\pi\backslash\lambda$ is the wave number, $d_x\ and\ d_y$ are the spacing between elements along each axis, θ is the elevation angle, and φ is the azimuth angle. These terms ensure that the array's geometry and the signal direction are accurately represented in the array factor. The numerator in (2) accounts for the constructive and destructive interference of the signals from multiple elements. At the same time, the denominator normalizes the pattern based on the number of elements ($M\ and\ N$) and their spacing.

Considering the received signal has azimuth and elevation angles, with directions of arrival, the ($N \times M$) planar array collected D signals, and the received signal could be written as shown in (5) and (6) [18]:

$$x = [a(\theta_1, \varphi_1) a(\theta_2, \varphi_2) \ldots a(\theta_d, \varphi_d)] \begin{bmatrix} S_{1(t)} \\ S_{2(t)} \\ \cdot \\ \cdot \\ S_{d(t)} \end{bmatrix} + n(t) \qquad (5)$$

$$x = AS(t) + n(t) \qquad (6)$$

Where A is the array steering vector corresponding to the direction of arrival, $s(t)$ is the desired signal beam, and $n(t)$ is the added noise beam.

DOA estimation and adaptive beam forming algorithms rely on the covariance matrix in array signal processing. For the complex signal received by the array, if considering (4), the covariance matrix is given by (7) [19]:

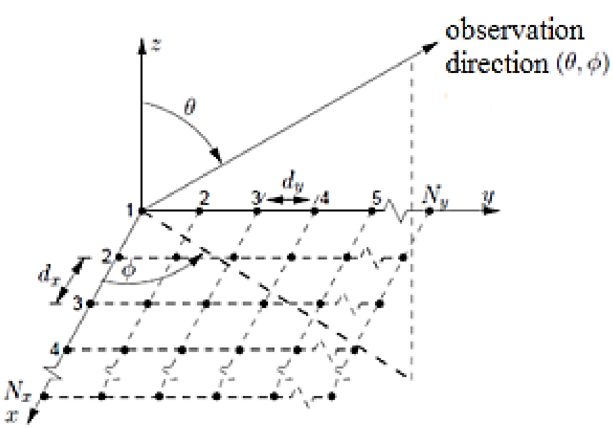
$$R_x = E[X.X^H] \qquad (7)$$

E is the mathematical expectation, and H is the complex conjugate transpose.

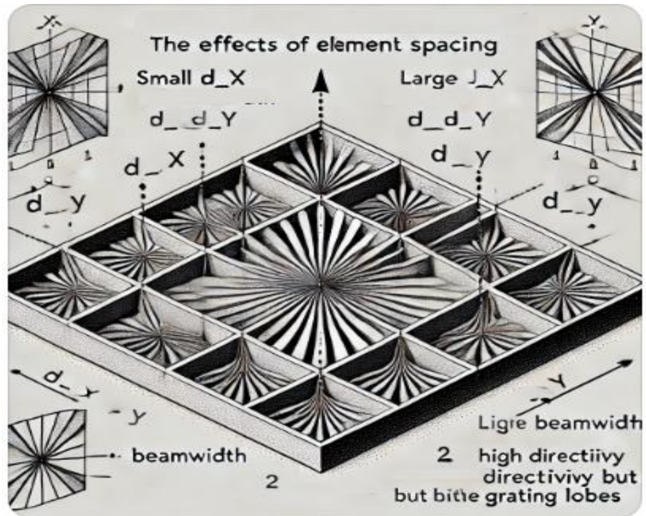
Considering that the signal and noise are uncorrelated and that the noise is white Gaussian noise, substitute the value of $x(t)$ from (8) [20]:

$$R_x = E\,[(AS+n)(AS+n)^H]$$
$$R_x = AE[SS^H]A^H + E[nn^H]$$
$$R_x = AR_{ss}A^H + R_n \qquad (8)$$
$$R_x = AR_{ss}A^H + \sigma_n^2 I$$

R_{ss} is the signal correlation, R_n is the noise correlation, σ is the noise variance, and I is the identity matrix.



(a) Uniform planar array geometry [21].



(b) Uniform planar array geometry with increasing and decreasing d [21].

Figure 2. Comparison of Uniform Planar Array Geometries

2.3 The 2D- ESPRIT Algorithm:

The Estimation of Signal Parameters via Rotational Invariance Techniques (ESPRIT) algorithm [22] inherits the displacement invariance property of sensor arrays to acquire significant computational benefits corresponding to traditional methods such as MUSIC (Multiple Signal Classification). Displacement invariance points out that the array impact stays unchanged under spatial rotations as long as the relative positions of the sensors are kept. This property permits ESPRIT to employ the array's configuration to reduce computational complexity [23].

Esprit algorithm decomposes the covariance matrix into several matrices each of which is the outer product of an eigenvector of the covariance matrix, the number of eigenvectors is equal to the array dimensions therefore by using the (6)-(8), estimated directions are calculated from the imaginary part or the real part using (9), and (10):

$$\Theta{\sim}k = sin - 1\left[\frac{\lambda < \varphi}{2\pi|\Delta 1|}\right] \qquad (9)$$

$$\gamma{\sim}k = sin - 1\left[\frac{\lambda < \varphi}{2\pi|\Delta 2| cos\Theta k}\right] \qquad (10)$$

Where $k \sim \theta$ is the azimuth angle estimate and $\gamma{\sim}k$ is the elevation angle estimate. λ is the wavelength in meters, $\Delta 1$ is the distance separation between the sub arrays in the azimuth plane, $\Delta 2$ is the distance separation between the sub arrays in the elevation plane, and $(k = 1,2,3 \ldots . K)$, where K is the total number of sources. These steps are repeated for each assumed source for different cases, changing the number of snapshots, the correlation factor, the signal-to-noise ratio, and other factors. Then the Root Mean Square error RMS in degrees, obtained from both the Azimuth and the Elevation angles, is calculated as shown in (11) [24]:

$$RMS - error = \sqrt{\left(\frac{\left(\Theta_1 - \widetilde{\Theta_1}\right)^2 + \left(\Theta_2 - \widetilde{\Theta_2}\right)^2 + \cdots \left(\Theta_k - \widetilde{\Theta_k}\right)^2}{(K * numberoftrials)}\right)} \quad (11)$$

2.4 Genetic Algorithms (GA)

Genetic Algorithm [25] is an evolutionary optimization technique inspired by natural selection and Mendel's laws of inheritance. It operates by mimicking the natural evolution process, encoding the solutions as chromosomes, and improving them iteratively through a selection, crossover, and mutation operation. This strategy particularly effectively finds near-optimal solutions in complex, large-scale problem spaces. The GAs can be computational because of the number of parameters involved in encoding and processing [26]. The Algorithm typically begins by randomly generating an initial population of solutions, evaluating their fitness, and iteratively producing new generations through genetic operators to improve solution quality.

As shown in Fig.3, the genetic Algorithm proceeds with the mutation function, which introduces variations by replacing the least fit solution in the population with a newly generated one. This step aims to promote diversity and prevent premature convergence. The process then repeats itself in evaluating solutions, applying crossover and mutation, and updating the population. These steps are repeated until a predefined stopping criterion is met, ensuring that the Algorithm converges towards an optimal or near-optimal solution, as outlined.

```
Initialize (P, c) // initialize the population
while (the termination condition is satisfied) do
Evaluate (P)
Selection (P) // select best fitness.
Crossover (P, C) // to produce new solution
Mutation (P, C) // replace worst solution with best one
end while
return Best // return best solution
```

Figure 3. Pseudocode of the Genetic Algorithm

3. Planar Array Antenna Element Optimization

This study adopts the ESPIRIT algorithm to improve signal orientation and attendance estimation [27], [28]. An algorithm was used to determine two angles, azimuth and elevation, using a planar sensor array. The advantage of this system is that it can simultaneously cover two layers, one specified for azimuth and the other for elevation. This improvement is significant over linear sensor arrays[29], [30] that select only one plane on the internal axis. Simulations were performed using Python, allowing the researchers to streamline the experiments and analyze the results. This approach aims to provide more accurate and efficient simulation results to reduce the performance of the ESPIRIT technology by using a planar sensor array. Research shows that this improvement in matrix design contributes to angle estimation accuracy, and signal reception generally improves[31]-[35].

Even though ESPRIT offers a solid and effective method for estimating angles, other optimization approaches, such as GA, might be explored. GA is considered a strong search that can explore a large set of potential solutions that could lead to the optimal or quasi-optimal solutions of a given complex problem. In signal processing applications, GAs can be used to find solutions for optimizing either the parameters of the sensor array or signal processing algorithms. However, in most cases, GAs are more computationally expensive than ESPRIT.

To further enhance ESPRIT's performance in an adverse environment subject to noise and interference, a suggested exploration would be to combine ESPRIT with GA into a hybrid scheme. This scheme could also use GA to pre-process the signal or optimize its parameters for the ESPRIT algorithm. This scheme ideally might achieve more accuracy and robustness compared to pure ESPRIT. However, this hybrid scheme yields additional complexity from the implementation and computational load points of view. Hence, the possible performance advantages are compromised against the natural costs [36].

This method systematically describes the steps for providing advanced signal-to-result direction estimation using the ESPRIT system:

- **Building the Equally Spaced Array**

A Gaussian distribution is used to construct 2D models to generate a covariance matrix. The dimensions of the matrix $(\mathrm{M1xM2})$ are determined based on the number of images (N).

- **ESPIRIT Calculation:**

The ESPIRIT algorithm estimates the angle of the received signals. This process is repeated $(\mathrm{n_r})$ times to obtain the error matrix.

- **Angle Estimation**

The face of each signal is computed based on the uniform structure of the matrix.

- **Fitness Function**

The performance of parameter sets $(\mathrm{K,\ N, M1, M2, and\ n_r})$ is evaluated using the ESPIRIT algorithm to estimate azimuth and elevation angles. The genetic Algorithm computes the RMS error between the estimated and model angles and minimizes it to determine the optimal parameter set.

- **Genetic Algorithm Integration**

Using a genetic algorithm, the parameters $(\mathrm{K,\ N, M1, M2, and\ n_r})$ have been optimized to reduce the RMS errors obtained from the ESPIRIT algorithm. The process requires starting with several chromosomes with random parameter values in a particular range, using the ESPIRIT algorithm to search each chromosome to calculate the mean RMS error, selecting to create a new population, making crossovers and mutations repeat for generations.

- **Parameter Optimization Function**

This function sets parameter ranges and genetic algorithm parameters, invokes the function, and prints the best parameters found. The objective of the genetic Algorithm is to find the best values for K, N, M1, and M2 that result in the most accurate forward estimation using the ESPIRIT algorithm. Fig.4 shows the genetic Algorithm combined with ESPIRIT.

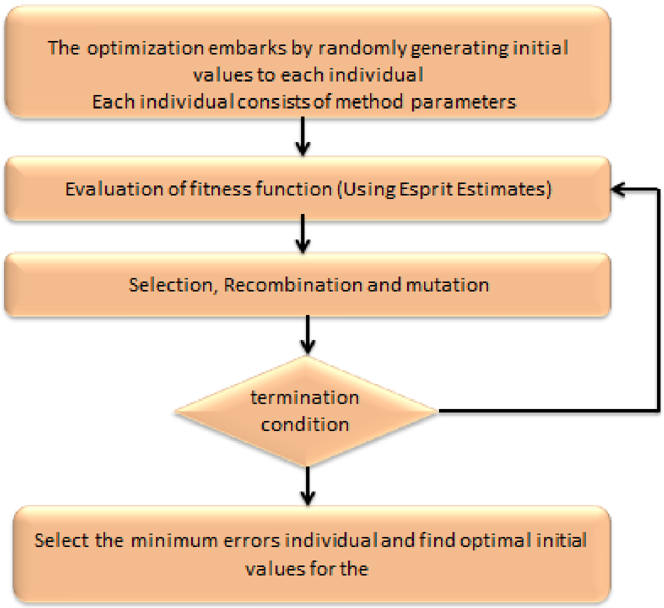


Figure 4. Improving ESPRIT algorithm through GA.

4. Experiment and Results

4.1 Parameters Settings of the Proposed Method

In an effort to improve the accuracy of estimating the direction and arrival of signals, the research comes up with an innovative technique that combines the ESPIRIT algorithm with genetic optimization. Combining these two powerful methods allows ESPIRIT to enhance its performance by optimizing the key parameters of the Algorithm. In this context, we will review some of the key applications of this state-of-the-art technology, which contribute to understanding the dynamic interaction between genetic design and ESPIRIT and how to improve its accuracy breed. Table 1 presents the parameters used for the genetic optimizer algorithm to optimize the ESPIRIT.

Table1. Parameters GA For optimization ESPIRIT

Parameter	Value
Number of generations	50
Number of solutions to be selected as parents in the mating pool	10
Mutation Probability	0.1
Crossover Probability	0.7
Type of parent selection	Singles -point

The results of the combination of the genetic algorithm and the ESPIRIT algorithm show a significant improvement in the algorithm's performance. In the 50th experiment, the best solution was found with a Best Fitness value of about 63.81. This means that combining genetic aspects with the ESPIRIT algorithm led to a solution that significantly improves the estimation of the direction and arrival of signals. Based on the results obtained after the fitting process between the genetic Algorithm and ESPIRIT, the best values of the algorithm parameters were found. These values are shown in Table 2, which displays the best values for the parameters that gave the least error.

Table 2. Best value of the planar array.

Attributes	Value
Number of target (K)	2
Number of time snapshots (N)	85
Number of time snapshots (N)	85
Number of rows of sensors (M1)	8
Number of columns sensors (M2)	3
Number of repetitions ($\boldsymbol{n_r}$)	10,20,30

These values are considered best based on the Best Fitness value relating to the solution with the specified characteristics (Best Solution) $[K, N, M1, M2, n_r]$. These values are shown to be effective for improving the accuracy of estimating the direction and arrival of signals using the combination technique between the genetic Algorithm and ESPIRIT.

4.2 Simulation and Discussion Results

For illustration, we employed 2-D DOA estimation based on the proposed approach. We set $M1 = 8$ and $M2 = 3$ from the genetic Algorithm, leading to an array configuration antenna. In addition, $k2$ is assumed. k far-field sources with identical power are assumed to be on the elevation-azimuth plane (θ_K, φ_K), where $\theta_K \in [0^o, 90^o]$ and $\varphi_K \in [-90^o, 90^o]$, for $k = 1, \cdots, K$.

We first examine the estimation accuracy in Figs.5, 6, and 7. The average root mean square error (RMSE) of the estimated azimuth and elevation angles with different SNR (10,20,30), respectively, expressed as (12) and (13):

$$RMSE_\theta = \sqrt{\frac{1}{IK}\sum_{i=1}^{I}\sum_{k=1}^{K}\left(\hat{\theta}_k(i) - \theta_k\right)^2} \quad (12)$$

$$RMSE_\varphi = \sqrt{\frac{1}{IK}\sum_{i=1}^{I}\sum_{k=1}^{K}(\hat{\varphi}_k(i) - \varphi_k)^2} \quad (13)$$

Those parameters are used as the performance metric, where $\hat{\theta}_k(i)$ and $\hat{\varphi}_k(i)$ are the estimates of θ_K and φ_K for the ith Monte Carlo trial, $i = 1, \ldots, I$.

The results show that increasing the number of sensors $(\boldsymbol{M}, \boldsymbol{N})$ significantly improves accuracy up to a threshold, $(\boldsymbol{e.g.}, \boldsymbol{M} = \boldsymbol{10})$, beyond which the accuracy gain diminishes while computational complexity rises sharply. Similarly, increasing the number of snapshots enhances accuracy under low SNR conditions but exhibits diminishing returns above 100 snapshots. For practical implementations, the configuration $\boldsymbol{M = 8, N = 3}$ with 85 snapshots offers an optimal tradeoff, achieving a low RMSE of 0.2 degrees while maintaining reduced computational costs. These findings demonstrate the suitability of the proposed method for embedded or resource-constrained radar systems.

Fig. 5 presents the Root Mean Square Error (RMSE) of the estimated elevation and azimuth angles for an SNR of 10 dB. Two subplots show how the number of snapshots used affects the estimation accuracy. Fig.5 (a) shows the RMSE of the elevation angle versus several snapshots; in Fig.5 (b), the RMSE of the azimuth angle versus several snapshots is shown. We observe from the figure that estimation accuracy increases significantly with an increase in the number of snapshots, that is, RMSE decreases substantially when we increase the number of snapshots vastly from 1 to about 80, but after approximately 80 snapshots, the improvement starts stabilizing, indicating a tradeoff between performance and computational cost. Another observation made in this context is that the elevation angle estimation shown in Fig.5 (a) experiences a smoother decreasing trend of RMSE, while the azimuth angle estimation in Fig.5 (b) becomes highly sensitive to noise and, thus, requires a greater number of snapshots to achieve stability. The importance of Fig. 5 resides in confirming an optimal number of snapshots for improved accuracy with reasonable computational complexity, thus corroborating the configuration selected herein (M = 8, N = 3, 85 snapshots) as a good compromise between accuracy and cost. In addition, it further reveals that GA-ESPRIT outperforms conventional methods based on MUSIC and PARAFAC, especially in low SNR scenarios. This affirms that the improved estimation accuracy resulting from using GA-ESPRIT with an optimal number of snapshots makes it very useful for practical applications in embedded radar systems.

Research has shown that the performance of 2D-DOA estimation improves with an increase in the number of antennas, denoted as M, as seen in studies [33], [7], and [34]. Several algorithms have been used to enhance DOA estimation, and it was observed that higher M values contribute to greater efficiency. However, an increased M significantly raises computational complexity. It is hence important to strike a balance between accuracy and complexity. Our approach leverages GAs to find the optimal M value, thus achieving comparable performance improvements without unnecessarily increasing M. Below is Table 3 with a summary of the performance comparison of our method against the existing approaches.

Table 3 shows that the proposed method achieves comparable or better performance in terms of RMSE, particularly at lower SNR levels, compared to state-of-the-art methods such as MUSIC and PARAFAC. The GA-optimized ESPRIT algorithm requires fewer sensors, reducing hardware complexity and cost. While MUSIC offers high resolution, its computational demands increase exponentially with the number of sensors, making it less suitable for real-time applications. Similarly, PARAFAC, while computationally simpler, struggles with accuracy under low SNR conditions or when the number of snapshots is limited.

Our approach effectively balances this tradeoff, achieving significant reductions in computational cost while maintaining high accuracy. This makes it highly suitable for embedded systems or portable radar solutions where both performance and resource constraints are critical considerations.

Table 3. Performance comparisons with 85 snapshots

Methods	$M_1 * M_2$	RMS (10 SNR)	RMS (20 SNR)	Computational Complexity	Real-Time Feasibility
Proposed Method	8 * 3	0.2	0.2	$O(n^2)$	High
[33]	10 * 10	1	0.7	$O(n^3)$	Low
[7]	8 * 10	0.5	0.1	$O(n^2)$	Medium
[34]	9 * 9	1	0.5	$O(n \log n)$	Medium

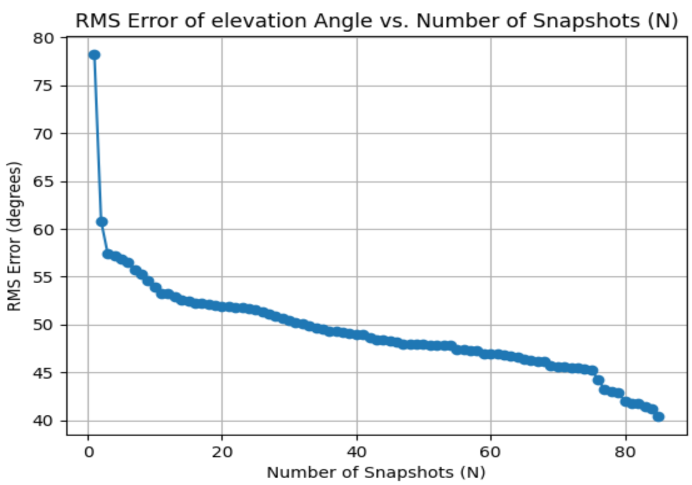
4.3 Discussion: Computational Feasibility and Future Directions

In this work, the optimal size of the antenna array, defined as the best number of sensors, was determined using Genetic Algorithms (GAs). This approach balances accuracy in Direction of Arrival (DOA) estimation with resource efficiency. However, the iterative computations inherent in GAs can pose significant challenges, particularly for real-time radar systems with critical latency and computational efficiency.

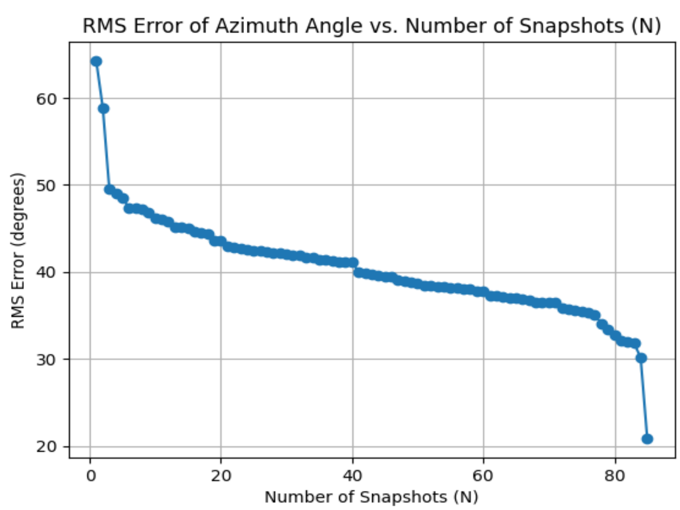
To address these computational demands, hardware accelerators such as Field Programmable Gate Arrays (FPGAs) and Graphics Processing Units (GPUs) offer promising solutions. These platforms are designed for high-performance parallel processing, enabling them to efficiently execute computationally intensive tasks such as GA operations and matrix calculations required by algorithms like ESPRIT. By leveraging these accelerators, the execution time of the optimization process can be significantly reduced, enhancing the system's feasibility for deployment in real-time radar applications.

Future work will focus on implementing the optimization algorithm on FPGA or GPU platforms to quantitatively evaluate its impact on computational performance. Additionally, exploring lightweight deep learning models as alternative optimization approaches could provide further enhancements, particularly in applications requiring adaptive or dynamic optimization. These advancements aim to mitigate computational constraints and improve the practicality of the proposed system for real-world use.

In this study, we employed Genetic Algorithms (GAs) to optimize the configuration of planar antenna arrays. GAs were chosen due to their proven ability to efficiently handle complex, nonlinear optimization problems. While this research focuses exclusively on GAs, we recognize the potential of alternative optimization techniques, such as Particle Swarm Optimization (PSO), Simulated Annealing (SA), and Ant Colony Optimization (ACO), as well as emerging methods like deep learning-based optimizations. Future work will explore these methods to compare accuracy, computational complexity, and real-time feasibility comprehensively.

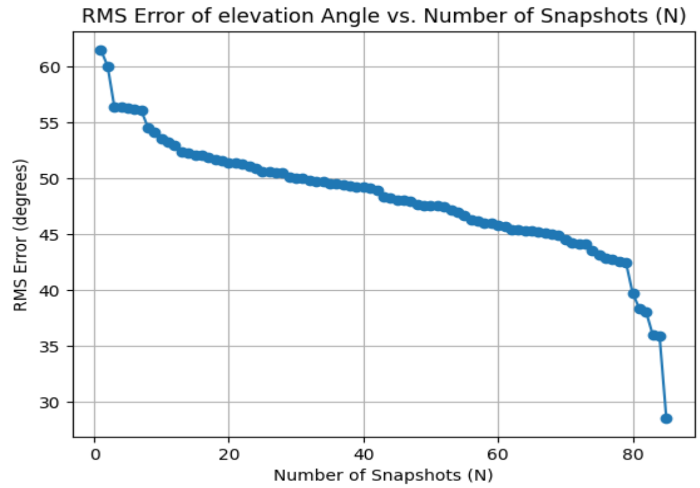


(a) SNR10 (dB): RMS of the Elevation angle versus the SNR

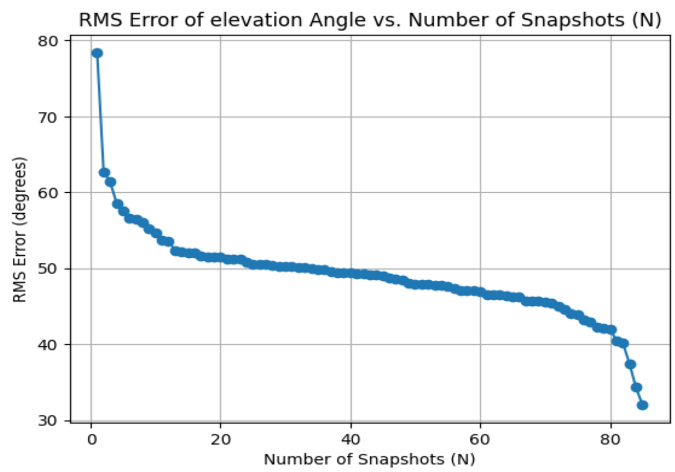


(b) SNR10 (dB): RMS of the Azimuth angle versus the SNR

Figure 5. RMS Error Analysis of Elevation and Azimuth Angles at SNR 10 Db

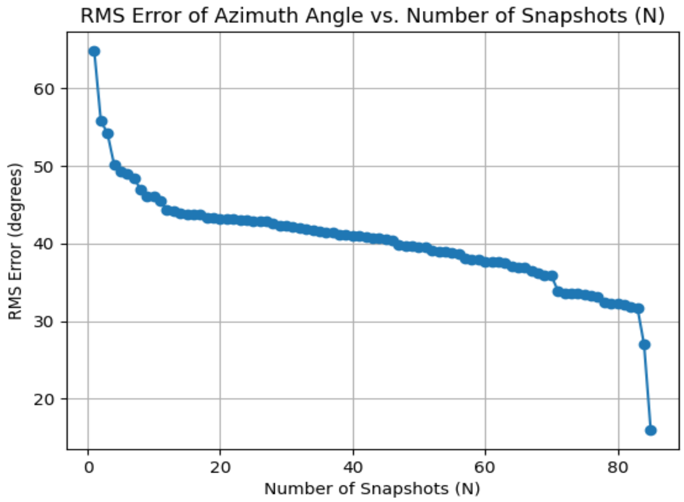


(a) SNR20 (dB): RMS of the Elevation angle versus the SNR

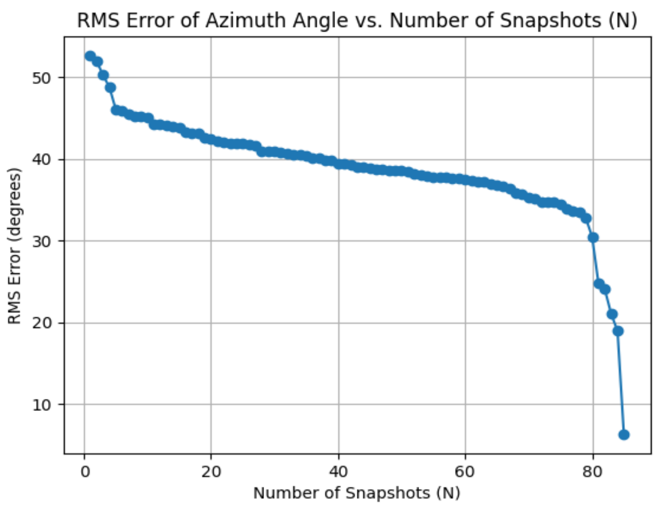


(b) SNR20 (dB): RMS of the Azimuth angle versus the SNR

Figure 6. RMS Error Analysis of Elevation and Azimuth Angles at SNR 20 dB



(a) SNR30 (dB): RMS of the Elevation angle versus the SNR



(b) SNR30 (dB): RMS of the Azimuth angle versus the SNR

Figure 7. RMS Error Analysis of Elevation and Azimuth Angles at SNR 30 dB

5. Conclusion

This paper presented a new method for optimizing planar antenna array configuration using a Genetic Algorithm methodology and represented one of the first applications of GA in this area. The work focused on using planar antenna arrays in radar systems, mainly for estimating the DOA of an incoming signal, including both azimuth and elevation angles. The research has employed the ESPRIT algorithm and systematically analyzed the effect of planar array design parameters, showing that optimizing the number of elements on each axis significantly improves the estimation accuracy without losing computational efficiency. The key contribution of this work is to utilize GA to determine the optimal number of array elements. Results show that a configuration with three elements along the x-axis and eight elements along the y-axis gives the best tradeoff between accuracy and system efficiency. This approach offers a great insight into radar system design, showing how algorithmic optimization can be combined with practical engineering. However, the proposed method is not without its limitations. Ideal conditions have been assumed in this study, which does not fully account for real-world factors such as environmental interference, hardware imperfections, or dynamic signal variations. Besides, the computational demands of GA-based optimization, though reduced, may still be challenging for large-scale or time-sensitive applications. In this regard, future work will concentrate on including hardware imperfections and environmental noise in the optimization process to estimate the robustness of the approach in realistic conditions. Second, using hardware accelerators, such as FPGAs or GPUs, may further facilitate real-time implementation. These directions aim to refine the proposed method further and expand its applicability to complex and resource-constrained radar systems.

Conflict of Interest

The authors declare that there are no conflicts of interest regarding the publication of this manuscript.

Author Contribution Statement

Malik Jasim Farhan conceptualized the research problem and defined the study objectives.

Methaq Kadhum formulated the theoretical framework, designed the methodology, and implemented the computational models.

Enas Rawashdeh validated the analytical methods, conducted the investigation, analyzed the data, and provided supervision throughout the research process.

Methaq Kadhum and Enas Rawashdeh critically discussed the findings, contributed to interpreting results, and played a significant role in drafting, reviewing, and refining the final manuscript.

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