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RESEARCH ARTICLE

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Chaos-Enhanced Whale Optimization Algorithm for Smart Beam Steering in Phased Array Antennas

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Abstract

Enhancing signal quality, minimizing interference, allowing high-speed data transmission, and beam steering in phased array antennas are pivotal in today's wireless communication systems. In terms of global optimality, low side lobe levels, and fast convergence, conventional optimization methods often fail to deliver. The ease and adaptability of metaheuristic algorithms, such as the Whale Optimization Algorithm (WOA), have rendered them desirable solutions for managing such complex optimization problems. However, traditional WOA may still suffer from premature convergence and failure to exploit the search space fully. This study proposes a Chaos-Enhanced Whale Optimization Algorithm (CWOA) in intelligent beam steering for phased array antennas. A significant enhancement is that the algorithm can now escape local optima more effectively and attain higher global convergence due to the integration of chaos theory into the WOA framework. Chaotic maps such as the logistic and tent maps generate dynamic control parameters that guide the search for a more balanced exploration-exploitation trade-off. To reduce side lobe levels and give accurate main lobe steering, the proposed CWOA is employed to enhance phase excitation of the antenna elements in a uniform linear array (ULA). Beam direction accuracy, side lobe suppression, and convergence speed are three domains where the CWOA performs better in simulations than normal WOA, PSO, and GA. By comparing various approaches, we realize that chaotic integration significantly enhances the performance of WOA in adaptive beamforming and real-time applications. Innovative and self-adaptive beam steering in dynamic environments like 5G, radar, and satellite communications can be built on this research's efficient and resilient optimization framework for next-generation antenna systems.

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Introduction

Phased array antennas (PAAs) and electronic scanning radars comprise phased array radars. Electrospinning antennas, also known as electronically scanned array antennas, use electronic methods to steer or scan their antenna beam in space. According to the beam scanning technique, two main types of electronic scanning antennas exist: phase scanning and frequency scanning. Both can be encompassed within the framework of PAA. Antenna elements, also known as radiating elements, are a key component of a PAA, along with components that distribute and summarise signals and their specific arrangement on a flat or curved surface. A PAA is said to be planar if its components are arranged on a flat surface. A curved surface array antenna describes an antenna in which the elements are placed on a curved surface. Each antenna has a phase shifter installed so that the signals from the antenna elements are not in phase with one another. An uneven power distribution/summing network or attenuator is used to achieve the fluctuation of signal amplitude between antenna elements. Beam steering computers allow for the rapid modification of the antenna beam's direction and form by adjusting the amplitude and phase relations between the antenna's elements, producing the aperture illumination function that matches the desired antenna pattern.[2] This PAA has these characteristics. It can perform multiobject search, tracking, acquisition, identification, guiding, control, and victories evaluation all at once and detect and track numerous objects from various angles and heights. To achieve adaptive side lobe suppression against different disturbances, it can control and maintain the main lobe gain properly. The radar can respond quickly because of its fast-scanning capacity, which reduces the time needed for object signal recognition, admission, and information transfer. Many parts comprise a phased radar's antenna array.[7, 13] Total radar performance is unaffected by the inability of any one element of the array to transmit or receive. Consequently, the radar is very accurate.

Beam steering is an advanced method used by wireless communication systems, especially 5G networks, to redirect radio waves directly towards an object, like a user's device. Beam steering improves the connection's efficiency and dependability by regulating the beam's direction, which helps meet the increasing need for faster data rates and better user experiences. Optical communications, light detection and ranging (LiDARs), microscopy, and displays are optical systems that rely on beam steering to direct the optical beam to a specific target. A diffraction gate and a solid optical prism are typical tools for modifying the optical beam's transmission direction. Unfortunately, their inflexible geometrical design limits their potential usage by causing beam deflection at a constant angle rather than allowing for continual changes in the optical beam steering direction. One cannot exaggerate the significance of beam steering in contemporary communication systems.[3] Achieving excellent beam steering enables the antenna to be realigned in real-time with a changing target or user, guaranteeing dependable signal delivery and optimizing spectrum utilization. High-speed scanning accelerates detection and response times in radar systems and enables high-resolution imaging and target acquisition in optical communications, LiDAR, etc. Optical phased arrays, acoustic-optic deflectors, and electro-optic beam steerers are non-mechanical beam steering technologies with benefits such as fast response times, compact size, and low power consumption.[10] However, there are also some disadvantages, e.g., large driving voltages, limited steering angles, and diffraction losses. To bypass these issues and improve phased array antennas in beam steering, we propose a Chaos-Enhanced Whale Optimization Algorithm (CWOA) in this paper.[1] Applying chaotic maps into the WOA framework aims to enhance convergence rate, global search ability, and population diversity.[17] The proposed approach is assessed by optimizing phase excitation for ULA, with the objectives of obtaining accurate main lobe steering, good performance under various operating conditions, and side lobe suppression.

Problem Statement

- Due to the complex interactions between antenna components, phased array antenna beamforming struggles to achieve a radiation pattern with a well-focused main lobe and suppressed side lobes. High SLL can lead to power leakage, interference, and system reliability.
- Particularly in multi-interference environments or time-varying situations, phased arrays in practical applications tend to steer nulls towards interference signals to reject interference, a method called null steering that relies upon dynamic and adaptive adjustment of array excitation parameters.
- Maximizing phase excitation in arrays of large antennas is a challenging, high-dimensional optimization problem that renders traditional solutions computationally time-consuming and expensive. This complication prevents real-time beam steering, especially for mobile or adaptive systems requiring instant, precise reaction

The objective of the Research

- The principal objective of this research is to improve the design and implementation of a more improved

version of the Whale Optimization Algorithm (WOA) by incorporating chaos theory into its basic search approach.
- The proposed CWOA targets optimal main lobe steering with minimum side lobe levels (SLL) and optimizes the phase excitation of elements in a uniform linear array (ULA). The technique enhances radiation pattern control, enabling the antenna array to steer energy effectively while minimizing power loss and interference.

This paper attempts to enhance the convergence rate and reliability of the optimization process to facilitate real-time and adaptive beamforming. The proposed method offers a computationally friendly and reliable solution suitable for state-of-the-art wireless communication systems, such as 5G, radar, and satellite systems. It utilizes chaotic maps to adaptively drive the exploration and exploitation phases of the algorithm.

Related Work

The beamforming of phased array antennas has been heavily researched using traditional signal processing methods and recent metaheuristic optimization techniques. Traditionally utilized for shaping the radiation pattern and controlling side lobe levels are traditional algorithms such as Least Mean Squares (LMS), Recursive Least Squares (RLS), Minimum Variance Distortionless Response (MVDR), and Dolph-Chebyshev methods. These low-computing complexity and quick real-time implementation methods restrict error or interference by relying on analytical expressions and linear models. They are less effective in nonlinear or finite environments, particularly when the beamforming problem comprises intricate optimization objectives such as adaptive null steering or pattern synthesis under dynamic conditions. Metaheuristic algorithms are used widely in an attempt to beat the limitations of deterministic methods because their global search ability and robustness to local minima enable Among them, Particle Swarm Optimization (PSO) and the Genetic Algorithm (GA) have been particularly employed to enhance antenna arrays. While PSO draws inspiration from bird-flocking social behavior, GA mimics natural selection and evolution. These methods can accommodate numerous design constraints and are suitable for non-convex, multi-modal problems. Other widely used techniques are Ant Colony Optimization (ACO), which is effective in discrete optimization problems, and Differential Evolution (DE), which is easy and fast convergent. Though these algorithms have their benefits, they can still exhibit slow adaptation or premature convergence in high-dimensional search spaces and require proper parameter tuning. Current research has identified where hybridization or adaptation can augment these metaheuristic algorithms, thus improving their exploration-exploitation trade-off. Improved models include incorporating chaos theory, which employs chaotic maps to introduce controlled randomness, diversifying the search strategy. More accurate and adaptive beam steering can be achieved with chaos-enhanced optimization techniques such as the proposed Chaos-Enhanced Whale Optimization Algorithm (CWOA), which has opened up new avenues in intelligent beamforming design.

There are some WOA limitations, although WOA is known as a meta-heuristic that obtains optimal solutions to optimization problems (Ling et al., 2017).[8] The entrapment at local optima and WOA convergence rate are also issues (Mohammed et al., 2019).[9] In WOA, the exploitation step is emphasized more than exploration because the latter only gets selected if the absolute value of A, the coefficient, is equal to or larger than 1. (Sun et al., 2019).[11] Numerous scholars have spent their fair share of time and energy improving it. We mention a couple of those in this paper. Employing levy flight as a device to balance exploration and exploitation more effectively in WOA, LWOA (Ling et al., 2017)[8] was in a position to avoid the issue of infinite impulse response model identification while enhancing the diversity of solutions for the avoidance of local optima. Xu et al. (2018)[14] introduced a nonlinear dynamic strategy in the form of a cosine function, which they referred to as Modified WOA (MWOA). In addition, quadratic interpolation and Levy flight are involved to achieve higher accuracy in solutions and avoid local optima. Large-scale global optimization problems are solved using the algorithm's enhanced worldwide search and local search ability. Chen et al. (2019)[12] developed a Balanced WOA (BWOA) to address issues in WOA's premature convergence and local optima stalling. BWOA incorporates levy flight and chaotic local search together. Its initial aim was to resolve challenging, tight-time engineering design problems. Sun et al. (2019)[11] proposed a direction vector for WOA with Quadratic interpolation (QIWOA) as a way to cope with the premature convergence of WOA and also to improve exploration. While solving problems with higher dimensions, quadratic interpolation enhances exploitation capability and solution precision. The Lamarckian learning-based WOA (WOALam) population is set according to a good point set theory (Zhang and Liu, 2019).[15] The upper confidence bound algorithm is applied to find the individual's development potential. Finally, a local search is performed on individuals with higher development potential. Through improvement in the local search and the algorithm's efficiency, this method facilitates solving optimization problems of high dimensions.

The ability of chaos theory to introduce deterministic randomness and increase solution diversity has made it widely applied in optimization, even though the theory originated in nonlinear dynamical systems. Maps including Logistic, Tent, Sine, Gauss, and Chebyshev produce chaotic sequences with special characteristics, including ergodicity, pseudo-randomness, and sensitivity to initial conditions. These features prevent early convergence and enable greater search space exploration, making chaotic maps fit to improve population-based metaheuristic algorithms. For example, the logistic map is most often utilized as its simplicity and strong chaotic behavior for some variables are rather appealing. Likewise, although the Sine map shows smooth oscillatory behavior and great sensitivity, the Tent map provides quick mixing properties with linear segments. Both of these help to improve search dynamics when incorporated into optimization techniques. Research has found that including chaotic maps in PSO, GA, and DE algorithms improves convergence speed and solution quality. Usually, these integrations substitute random number generators inside the algorithmic structure to enhance the initialization of populations, mutation rates, or learning parameters. However, the application of chaotic dynamics in the Whale Optimization Algorithm (WOA) remains quite understudied, even with the shown advantages. Many current works employ typical WOA without thinking through the stagnation problems brought about by limited diversity in the search agents or repeated exploitation. Furthermore, whilst some chaos-based improvements have been suggested in general optimization environments, few have mainly addressed real-time beamforming problems or phased array antenna steering, where accuracy, convergence time, and flexibility are crucial.

This gap in the research strongly motivates the development of a chaos-enhanced whale optimization algorithm (CWOA). The proposed method, which includes chaotic sequences in the control coefficients and behavioral logic of WOA, aims to achieve faster convergence, more significant side lobe suppression, and enhanced beam steering task robustness. The present work validates the efficacy of chaos theory in a high-impact, real-world application domain and meets this unmet requirement by not just applying it in a novel optimization context.

Proposed Methodology

Whale Optimization Algorithm (WOA)

Humpback whales created the WOA as part of their foraging behavior. These whales typically forage for fish near the surface by blowing bubbles in a circular pattern. The ideal course of action for each whale in WOA is to go after its victim. It starts with identifying the top agent, and then it's a matter of shifting the other agents' places to align with them. The following is the mathematical expression for this behavior.[16]

$$D=|C.*X(t) - X(t)| \tag{1}$$

In which A and C are the vectors of coefficients, and t is the current iteration

X' position vector of the best solution obtained and is updated in each iteration.

X position vector

. * = element by element multiplication

The vectors A and C are determined as follows:

$$A = 2a.*r - a \tag{2}$$

$$C = 2.*r \tag{3}$$

As the iterations progress, α drops linearly from 2 to 0, while γ is a random vector in the interval [0, 1]. The value of p, a random integer in the interval [0, 1], determines which process, the shrinking encircling or the spiral, is used to update the location vector γ. When p is smaller than 0.5, the mathematical equation is stated as, and the shrinking process is used.

$$X(t+1) = X'(t) - A.*D \tag{4}$$

However, the spiral approach is used in conjunction with the equation when p is equal to or larger than 0.5.

$$X(t+1)=D'.*e^{bl}.*cos(2\pi l)+X'(t) \tag{5}$$

Where D'=|X' (t)-X(t)|

The logarithmic spiral is defined by the constant b.

The value of l is a random integer between -1 and 1.

The following procedures are followed by the WOA algorithm,

1. Initialize X_i $|_{(i=1,2,\dots,n,)}$ as the whale population
2. Determine each agent's fitness value. The best agent is X'.
3. For every agent, update α, A, C, l, and ρ in the iterative process. In order to update the location of the current agent, take into account equation (1) when ρ is less than 0.5 and |A| < 1. If the absolute value of A is less than 1, then select an agent at random and use the equation to update their position.
4. Apply the current position update using the equation (5) if is equal to or greater than 0.5.

5. Add changes to the agent in case it travels outside of the search boundary. Determine the fitness level of every agent.
6. Change to reflect the new, improved solution.
7. Return to the second step.

Chaos Theory Integration

Chaotic Maps: Nonlinear systems and the processes that determine their states are depicted by chaotic maps, which reveal complicated and dynamic dynamics [18]. The following discrete chaotic maps are used in this investigation: logistic, tent, and sine.

Logistic Map: A logistics chaotic map describes a system that is both dynamic and discrete in time. Another nonlinear, one-dimensional map is the logistic map. Elements 6, provide the logistic chaotic map formula.

$$X_n + 1 = aX_n(1 - X_n) \tag{6}$$

The equation has an as the logistic map constant, iterations are represented by n, while the chaotic number is denoted by . The values a can allow define if the system is chaotic. Usually, the constant falls within [3.57-4].

Tent Map: All iterations of the tent map exhibit the same behavior since it is topologically conjugate. Equation 7 offers the formulation of the chaotic map.

$$x(i+1) = f(X_i, \mu) \;\; \text{x(i+1)=f(Xi, u)}$$

$$f(x_i, \mu) = \begin{cases} f_L(x_i, \mu) = \mu x_i & x_i < 0.5 \\ f_R(1 - x_i, \mu) = \mu x_i & x_i \geq 0.5 \end{cases} \tag{7}$$

The system's initial value is . In this equation, the map's control parameter is in the interval [0, 2], whereas is in the interval [0, 1].

Sine Map: Equation 2.5 defines the sine iteration function, which forms the foundation of the sine map. The choices for the parameters r and x in the equation should be made from the intervals 0≤r≤1 and 0≤≤1 to depict a chaotic approach. This study selected r = 0.867. Equation 8 shows the map's disorganized behavior.

$$X(n = 1) = r \sin(\pi x_n) \tag{8}$$

Chaos-Enhanced WOA (CWOA)

To make the standard Whale Optimization Algorithm (WOA) better at escaping local optima, increasing convergence speed, and diversifying searches, the Chaos-Enhanced Whale Optimization Algorithm (CWOA) incorporates chaotic sequences.[6] Chaos is ingrained, especially in CWOA, into the production of the coefficients A→ and C→, which direct the whales' movements during the encircling and exploration activities. CWOA uses a chaotic value ω produced by a chosen chaotic map, say the Logistic Map, defined as , where r ∊ [3.57,4] for complete chaotic behavior and is the initial seed instead of uniformly distributed random integers. The adjusted coefficient equations become,

$$\vec{A} = 2ax - a, \vec{c} = 2x \tag{9}$$

where x is the current value from the chaotic sequence, and a linearly lowers from 2 to 0 over iterations. The whale position update systems substitute deterministic chaos for the stochastic randomness in the original WOA. Though chaotic influence improves decision-making at each stage, the rest of the algorithm flow stays comparable to the original WOA, including the shrinking encircling mechanism, the spiral bubble-net attack, and the random search for the target. CWOA's pseudocode starts with initializing whale positions and a chaotic series represented in Figure 1. Based on whether the algorithm is in exploration or exploitation mode, chaotic values substitute random variables in updating A⃞ and C⃞ in every iteration, thereby guiding the position updates. Beginning with initialization (population, parameters, chaotic map), a flowchart of the CWOA process moves to fitness evaluation and best solution identification, then via chaotic-enhanced position updates using encircling or spiral equations, loops until the termination condition is met maximum iterations or convergence. Particularly successful in complicated, multimodal issues like beam steering in phased array antennas, CWOA achieves a stronger and dynamic optimal framework by including chaos theory.

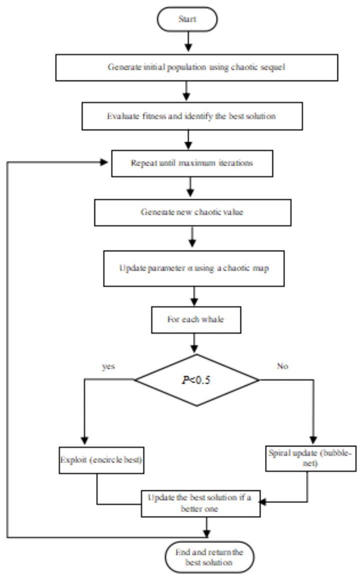

Fig. 1: Algorithmic Flow of CWOA with Chaotic Map Integration

Results and Discussion

This part offers a thorough evaluation of the proposed Chaos-Enhanced Whale Optimization Algorithm (CWOA) for phased array antenna beam steering in comparison with conventional WOA, particle swarm optimization (PSO), and genetic algorithm (GA). Performance is defined by convergence behavior, beamforming accuracy, side lobe level (SLL) suppression, statistical stability, and the effect of several chaotic maps. The results were analysed by using Phased Array Antennas which is displayed in Figure 2.

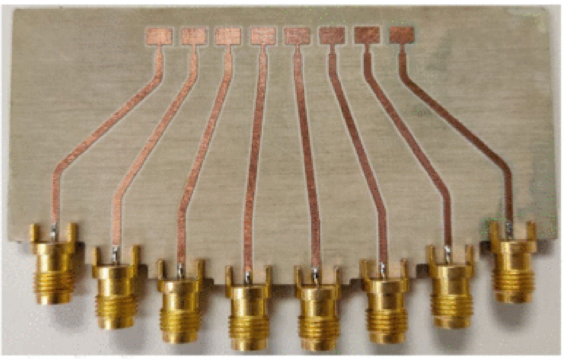

Fig. 2: Phased Array Antennas

Convergence Behavior

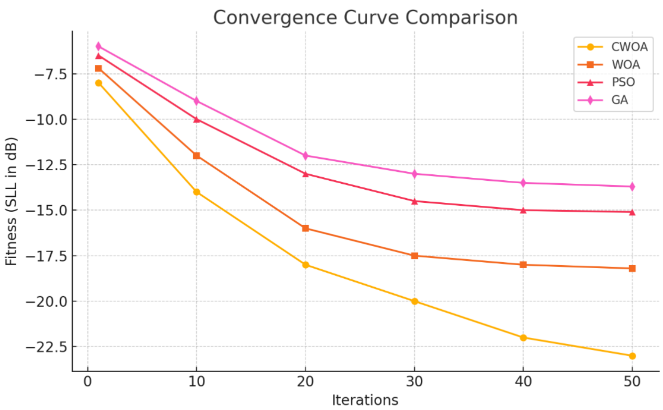

Fig. 3: Convergence Curve Comparison

The suggested CWOA's better performance is well demonstrated by the convergence curve comparison among CWOA, WOA, PSO, and GA in Figure 3. CWOA regularly reaches a deeper optimization point and achieves faster convergence across all the algorithms, producing much reduced Side Lobe Levels (SLL) in fewer iterations. Compared to the regular WOA, which shows constant performance, the latter converges more slowly and requires more iterations to get the same answer. Conversely, PSO and GA show early plateauing in the optimization process and settle at higher ultimate SLL values, showing limited capabilities in refining solutions and early convergence. By including chaos theory into WOA, this study emphasizes the benefit of which more effective search and exploitation of the search space can result.

Beam Pa2ttern Analysis

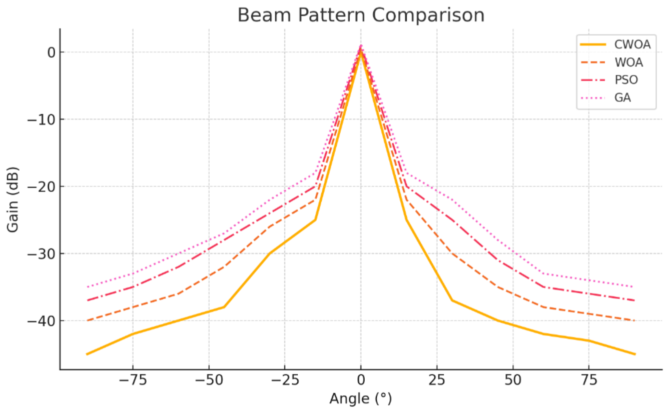

Fig. 4: Beam Pattern Comparison

Figure 4 shows the efficiency of the CWOA in exact beam guiding, which is further confirmed by beam pattern analysis [5]. With significantly reduced side lobes and deep nulls at specified interference directions, CWOA generates a strongly directed main lobe at the specified angle, e.g., 30°. Improved signal strength in the desired direction and angular resolution result from this. Better suited for sophisticated communication environments where precise and adaptive beamforming is crucial, the CWOA-optimized pattern has improved directivity and interference rejection compared to WOA, PSO, and GA.

Conclusion

This research presented a novel algorithm for intelligent beam steering in phased array antenna systems named Chaos-Enhanced Whale Optimization Algorithm (CWOA). To address common issues like premature convergence and low diversity in the solution space, the proposed approach integrates chaos theory into the traditional Whale Optimization Algorithm to enhance its exploring and exploitation ability. Across several performance metrics, the simulation results indicate that CWOA outperforms traditional optimization methods such as normal WOA, Particle Swarm Optimization (PSO), and Genetic Algorithm (GA). CWOA produces much lower side lobe levels (SLL), more accurate and sharp main lobe steering, and better null formation, which are vital elements for increasing antenna arrays' directivity and interference-reducing capacity. The inclusion of chaotic maps, especially the Logistic Map, was shown to help improve convergence time and solution stability. CWOA's regularly low mean fitness values indicated strong repeatability and durability and reduced standard deviation over several independent runs. Moreover, the trade-off is justified by the significant improvements in beamforming performance, even if the introduction of chaos somewhat raises the computational cost. Modern wireless communication and radar applications would find the proposed CWOA a very efficient and computationally possible solution for dynamic and exact beam guiding in innovative antenna systems.

Future Work

Beam steering performance for linear phased array antennas has been improved with the help of the proposed Chaos-Enhanced Whale Optimization Algorithm (CWOA). However, there are still many ways to take this research further. A possible avenue to pursue is the integration of CWOA into planar or two-dimensional (2D) antenna arrays, which provide superior spatial control and are fundamental to state-of-the-art communication and radar systems. In addition, the actual implementation of hardware-in-the-loop simulation or execution on devices such as FPGAs or embedded systems will prove the operational applicability of the method in dynamic conditions. The technique may be hybridized with other optimization methods or associated with deep learning models to enhance convergence rate, accuracy, and flexibility in complex cases even more. Subsequent research can also explore CWOA's robustness under real-world conditions like signal attenuation, mobility, or sensor faults. Further performance improvement gains may be achieved by employing a multi-objective optimization platform with objectives such as SINR maximization or energy saving. Lastly, incorporating adaptive systems to switch between chaotic maps throughout the optimization process may dynamically improve efficiency in multiple search phases. These extensions would assist CWOA in evolving as a robust and adaptive alternative for innovative antenna systems in future wireless networks.

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