Direction of Arrival Estimation Using Cray Fish Optimization Algorithm

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***Abstract*— Determining the direction of incoming signals is a crucial research subject in 4G and 5G communication. Many spectral and eigen structure methods can be used to determine the direction of narrow band bases. These approaches cannot forecast the path of the indicator while the channel is coherent and the signal to noise ratio stays low. Maximum Likelihood is a statistical technique for estimating that circumvents the drawbacks of traditional systems to detect and follow signals in challenging circumstances accurately. By using unspecified parameters to minimize the complex log likelihood function. The ML approximation is determined. The author of this chapter suggested the use of the Cray Fish Optimization algorithm to approximate the narrow band foundation path in a low signal to noise ratio situation. Swarm intelligence algorithm Cray Fish Optimization is capable of both exploration and exploitation. According to the simulation outcomes Cray Fish Optimization performs better in provisions of root mean square error and probability of resolution than both traditional methods and the sine cosine algorithm.**

***Index Terms*— ML, COA, SCA, RMSE, PR.**

I. INTRODUCTION

The technique of optimizing is determining the most optimal solution given the limitations that exist. It is the process of determining the best course of action given the circumstances. Numerous imperfections can be seen as barriers to optimization. Numerous methods for solving optimization problems have been created and have advanced dramatically during the previous few decades. A higher-level method for finding solutions in artificial intelligence and mathematical optimization, "Metaheuristic" [1] generates or chooses the fractional search strategy that can adequately explain an optimization problem, particularly in cases where computational power is limited, or data is uncertain and untrustworthy. Solutions that are large enough to sample completely makeup collections of metaheuristic samples. In contrast to optimization algorithms, which do not ensure that a globally optimal solution can be found for a given collection of problems, this method makes few assumptions about how the optimization problem will be addressed, making it potentially beneficial for a wide range of problems. Metaheuristics are rules for the search process. Determining the most efficient solutions requires a comprehensive exploration of the search field. Metaheuristic algorithms include simple local actions and complex learning strategies. Although they are typically non-deterministic and approximate, they are not excessively imprecise. A lot of metaheuristics make use of optimization in some way to guarantee that the solution is derived from a set of variables that are created at random. By considering a wide range of alternatives, metaheuristics can often find good answers with less computational effort than optimization techniques. Metaheuristic optimization algorithms have become more and more popular as an optimization strategy in recent years. Some of the most well-known algorithms in this field are genetic algorithms (GA) [2], particle swarm optimization (PSO) [3], ant colony optimization (ACO) [4], ant lion optimization (ALO) [5], differential evolution (DE) [6] and evolutionary programming (EP) [7], cuckoo search (CS) [8], firefly algorithm (FA) [9], and dragonfly algorithm (DA) [10].

To replicate the foraging, summer vacation, and rivalry patterns of crayfish, COA [21] recommended a novel methodology. The algorithm's capacity for exploration and exploitation is balanced by adjusting the temperature.

The target of coming approximation (DOA) [13–14] and adaptive beamforming (ABF) [15–16] are two key components in the wireless communication domain that are essential to smart antenna [17–18] and MIMO systems [19]. The authors of this chapter examined the effectiveness of the suggested algorithm for determining the direction of signals in varied SNR environments by optimizing the deterministic ML [20] function.

II. DATA MODEL

Let us assume a ULA with M-sensing components. The distance, d, between successive sensors equals half the wavelength of the signals that are received.

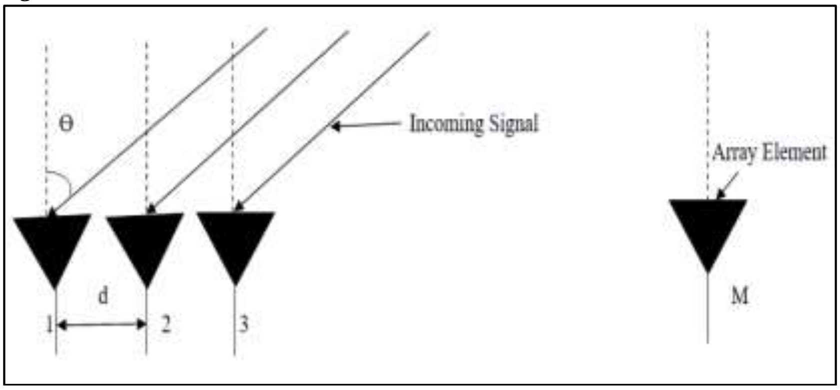

Fig. 1 Assume that the ULA is imposed by D narrow band far-field signal sources with unique DOAs

The array steering vector of size M X 1 represents the i^{th} user's direction as mentioned below, whereas the phase source is the first element of the ULA.

$$a(\theta i) = [1, z, \dots, z^{M-1}]^T, \quad z = e^{\left(\frac{j2\pi d}{\lambda}\right) sin\theta i} \qquad \text{Eq. 1}$$

Where λ is the originating signal's main wavelength and the angle observed from the array broadside is represented by θi. The entire signal that the array members have received at the time sample t^{th} can be expressed as follows:

$$\bar{x}(t) = \bar{A}(\theta) * \bar{s}(t) + \bar{n}(t) \qquad \text{Eq. 2}$$

Where the noise vector is indicated by $\bar{n}(t)$, the incident complex monochromatic signals are denoted by $\bar{s}$(t), and $\bar{A}(\theta)$ array steering vectors compose the array steering matrix, which is defined as follows:

$$\bar{A}(\theta) = [\bar{a}(\theta_1) \dots \bar{a}(\theta_D)] \qquad \text{Eq. 3}$$

Instead of using the actual array output x(t), correlation matrices are used for DOA estimation in array signal processing; the correlation matrix is defined by:

$$\overline{R_{xx}} = E[x.\overline{x^H}] = \overline{AR_{ss}}\bar{A}^H + \overline{R_{nn}} \qquad \text{Eq. 4}$$

Where E[],$()^H$signifies the expectation and Hermitian operation, respectively, and $\overline{R_{ss}}$ denotes the origin matrix and $\overline{R_{nn}}$ the noise correlation matrix. In this case, the deterministic approach for determining the direction of arriving signals was proposed by the authors. Consequently, the signal vector is predictable given unknown configurations. In the stochastic model, ML obtains the incoming signal's angle estimate, θ, through continuously enhancing the non-direct multimodal work, which is provided by:

$$f_{DML} = tr\ [(I_M - \bar{A}(\bar{A}^H\bar{A})^{-1}\ \bar{A}^H)\bar{R}] \qquad \text{Eq. 5}$$

Where M X M is the sequence of I_M and tr [] indicates the trace.

III. Conventional DOA Approximation Procedure

The standard DOA evaluation mechanism provides an appropriate representation in a deterministic high SNR scenario. It is a simple, effective, and less complex method. We illustrate these computations using both subspace and non-subspace methods. Subspace draws near, also known as Eigen structure strategies, deterioration of the cluster connection network into two subspaces of sign and clamor using Eigen deterioration to assess the approaching sign's bearing. Non-subspace strategies, also known as terrifying, assessment techniques, evaluate the acquired sign's course by observing the peak of the pseud-range. The methods used by Capon and Bartlett, two nonlinear spectral estimating techniques, differ in how the weights for synthesizing the pseudospectrum are determined. Several of the most important Eigen structure methodologies utilizing orthogonal signal subspaces for DOA estimation are ESPRIT, Root-MUSIC, MUSIC, matrix pencil, Pisarenko harmonic decomposition, as well as a min-norm estimate.

IV. Capon

A minimum variance distortion less response (MVDR) indicates what the Capon DOA approximation is. The objective is to send the signal of interest in phase and amplitude without distortion to maximize the signal-to-interference ratio (SIR). It is expected that the source correlation matrix ($\overline{R_{ss}}$) will be diagonal. A set of array weights ($\bar{w} = [w_1 w_2 \dots \dots w_M]^T$) is used to produce this maximized SIR. The array weights are arranged as follows:

$$\bar{w} = \frac{\bar{R}_{xx}^{-1}\bar{a}(\theta)}{\bar{a}^H(\theta)\overline{R_{xx}}^{-1}\bar{a}(\theta)} \qquad \text{Eq. 6}$$

In which $\bar{R}_{xx}^{-1}$ is the array correlation matrix. The information that follows is the pseudo spectrum: -

$$P_C(\theta) = \frac{1}{\bar{a}^H(\theta)\bar{R}_{xx}^{-1}\bar{a}(\theta)} \qquad \text{Eq. 7}$$

V. Music

Nevertheless, the traditional MUSIC method collapses whenever signal correlation becomes significant, necessitating the introduction of compensatory measures. One needs to either search the eigenvalues or estimate the total quantity of signals that arrive in anticipation. If there are multiple D signals (where M is the number of array items), then there are M-D noise eigenvalues and eigenvectors alongside the D signal eigenvalues and eigenvectors. Although MUSIC uses noise as an eigenvector subspace, it is sometimes referred to as the subspace technique. The following is the mathematical framework for MUSIC:

I. Compute the array correlation matrix ($\overline{R_{xx}}$) under the assumption that the noise has no correlation and has equivalent variances.
II. Next, determine the eigenvalues and eigenvectors for ($\overline{R_{xx}}$). D eigenvectors are subsequently used to indicate the signals, while M-D eigenvectors are used to symbolize the noise. The eigenvectors selected have the lowest possible eigenvalues. For unrelated signals, the lowest eigenvalues are equal to the variance of the noise. Following that, the noise eigenvectors' M × (M − D) dimensional subdomain can be built as follows:

$$\bar{E}_N = [\bar{e}_1 \ \bar{e}_2 \dots \ \bar{e}_{M-D}] \quad Eq.8$$

III. The array steering vectors at the angles of arrival $\theta_1, \theta_2 \dots, \theta_D$ are orthogonal to the noise subspace eigenvectors. The orthogonality constraint allows us to express the Euclidean distance as follows:

$$d^2 = \bar{a}(\theta)^H \bar{E}_N \bar{E}_N^H \bar{a}(\theta) = 0 \quad Eq.9$$

IV. Significant peaks show up at the arrival angles when the denominator is calculated using this distance formula. The following is the new MUSIC pseudo spectrum:

$$P_{MU}(\theta) = \frac{1}{|\bar{a}(\theta)^H \bar{E}_N \bar{E}_N^H \bar{a}(\theta)|} \quad Eq.10$$

V. Locate the sharply defined tops throughout the pseudo spectrum that corresponds to the appearance point of the approaching signals.

VI. Cray Fish Optimization

Inspired by the movement and feeding habits of crayfish, the Crayfish Optimization method (COA) is a population-based metaheuristic optimization method. Crayfish exhibit flexible locomotion patterns, alternating between exploitation (finding new solutions) and exploration (exploring new areas). This behavior is the basis for the CFO method, which finds optimal solutions in difficult optimization problems by combining angular turns with forward and backward motions.

VII. Population Initialization

Every crayfish in the multi-dimensional problem of optimization is a 1 × dim matrix. A problem's solution is represented by each column matrix. Each variable Xi in a collection of variables ($X_{i,1}$, $X_{i,2}$,…, $X_{i,dim}$) must fall between the upper and lower bounds. A set of potential solutions X is randomly generated as the COA's initialization in space. Based on population size N and dimension dim, candidate solution X is proposed. Eq.11 displays the COA algorithm's initialization.

$$X = [X_1, X_2, \dots, X_N] = \begin{bmatrix} X_{1,1} & X_{1,j} & X_{1,dim} \\ X_{i,1} & X_{i,j} & X_{i,dim} \\ X_{N,1} & X_{N,j} & X_{N,dim} \end{bmatrix} \quad Eq.11$$

Where $X_{i,j}$ is the position of individual i in the j dimension, N is the total quantity of populations, dim is the population dimension, and the value of $X_{i,j}$ is derived from Eq. 12.

$$X_{i,j} = lb_j + (ub_j - lb_j) \times rand \quad Eq.12$$

The variables lb_j and ub_j denote the lower and upper bounds of the jth dimension, respectively, and rand is a random number.

VIII. Describe The Crayfish's Consumption And Temperature

The crayfish will undergo numerous stages of behavior due to temperature changes. Eq.13 defines temperature.When temperatures rise above 30 °C, crayfish will choose a cool location for their summer vacation. The correct temperature will lead crayfish to begin feeding. The temperature influences how much crayfish eat. Crayfish have a feeding range of 15, 30, and 25 °C, which is ideal. Consequently, the crayfish feeding amount may be roughly compared to the usual distribution, indicating that temperature has an impact on the feeding amount, as temperatures range from 20 and 30 °C, crayfish exhibit robust foraging behavior. Accordingly, the COA specifies a temperature range of 20 to 35 °C. The crayfish intake mathematical model is displayed in Eq.14.

$$temp = rand \times 15 + 20 \quad Eq.13$$

Where, temp, is the ambient temperature of the crayfish's location.

$$p = C_1 \times \left(\left(\frac{1}{\sqrt{2 \times \pi \times \sigma}}\right) \times \exp\left(\frac{-1}{2\sigma^2}\right) \times (temp - \mu)^2\right) \quad Eq.14$$

While μ indicates the ideal temperature for crayfish, C1 and σ regulate the amount of seafood that is consumed at various temperatures.

IX. Exploration

The temperature is high enough when it exceeds thirty. The crayfish will now decide to explore within the cave. The cave X_{shade} is described as follows:

$$X_{shade} = \frac{(X_G + X_L)}{2} \quad Eq.15$$

Where X_L denotes the ideal location of the present population and X_G is the ideal location reached thus far based on the number of iterations. Crayfish battles over caves occur completely randomly. When the rand is less than 0.5, it indicates that there are no other crayfish battling for the cave, and the crayfish will enter the cave without delay to explore. At this moment, the crayfish will head into the cave for investigation using Eq. 16:

$$X_{i,j}^{t+1} = X_{i,j}^{t} + C_2 \times rand \times \left(X_{shade} - X_{i,j}^{t}\right) \qquad \textit{Eq. 16}$$

Where t denotes the iteration number of the current generation, t + 1 denotes the iteration number of the subsequent generation and C_2 is a curve that declines as described in the below Eq. 17.

$$C_2 = 2 - \left(\frac{t}{T}\right) \qquad \textit{Eq. 17}$$

Where T is the maximum quantity of loops that can be made.

Crayfish wants to get as close to the cave as possible during the exploring stage since it is the best course of action. The crayfish will now move towards the cave. This improves the capacity of COA to be exploited and brings participants closer to the best response. Facilitate a faster convergence of the algorithm.

X. Exploration

A combination of rand ≥ 0.5 and temp > 30 indicates the attraction of other crayfish in the cave. Now, they will attempt to capture the cave. The crayfish uses Eq. 18 to compete for the cave.

$$X_{i,j}^{t+1} = X_{i,j}^{t} - X_{z,j}^{t} + X_{shade} \qquad \textit{Eq. 18}$$

Where, according to Eq. 19: z stands for the randomized member of crayfish.

$$Z = \text{round}\ (\text{rand} \times (N-1)) + 1 \qquad \textit{Eq. 19}$$

Crayfish compete with one another at the exploitation stage, and crayfish X_i modifies their position in response to another crayfish's position (X_z). The position can be changed to increase the search range of COA and improve the algorithm's exploration capability.

The temperature is ideal for crayfish feeding when it is less than thirty degrees. The crayfish will now start to approach the meal. The crayfish will determine the size of the meal after locating it. Should the food be excessively huge, the crayfish will use its claws to break it up and use its second and third walking foot to consume it in turn. X_{food} is a food location that is described as:

$$X_{food} = X_G \qquad \textit{Eq. 20}$$

Q is the food size specified as:

$$Q = C_3 \times \text{rand} \times \left(\frac{fitness_i}{fitness_{\ food}}\right) \qquad \textit{Eq. 21}$$

Where $fitness_i$ is the fitness value of the ith crayfish, $fitness_{food}$ is the fitness value of the food location, and C3 is the food factor, which indicates the largest food. The value of C3 is fixed at 3. The largest food serves as the basis for the crayfish's estimation of food size. Q > (C3 + 1)/ 2 indicates that the meal is enormous. The crayfish will now use its first claw foot to tear the food as described below:

$$X_{food} = \exp\left(\frac{-1}{Q}\right) \times X_{food} \qquad \textit{Eq. 22}$$

The food will alternatively be picked up and placed into the mouth by the second and third claws as it shreds and gets smaller. A mixture of the sine and cosine functions is utilized to simulate the alternating process. Furthermore, the food consumption and the food that crayfish get are connected, therefore the search equation is as follows:

$$X_{i,j}^{t+1} = X_{i,j}^{t} + X_{food} \times p \times (\cos(2 \times \pi \times rand) - \sin(2 \times \pi \times rand)) \qquad \textit{Eq. 23}$$

The crayfish only needs to go in the direction of the food to eat it immediately when Q ≤ (C3 + 1)/ 2. The equation is as follows:

$$X_{i,j}^{t+1} = \left(X_{i,j}^{t} - X_{food}\right) \times p + p \times rand \times X_{i,j}^{t} \qquad \textit{Eq. 24}$$

Based on the size of their meal Q, crayfish employ a variety of feeding techniques throughout the searching stage, with food X_{food} serving as the best option. The crayfish will approach the meal when it is of a size that they can consume. When Q is excessively large, it suggests that the best solution and reality deviate significantly from one another. X_{food} should therefore be lowered and moved closer proximity to the food. COA will become closer to the ideal solution during the searching stage, improving the algorithm's exploitation and convergence capabilities.

XI. Sine-Cosine Algorithm

SCA is a stochastic optimization algorithm proposed by S. Mirjalili in 2015. The algorithm is inspired by the basic behavior of mathematical sine and cosine functions. In SCA a random initial solution is created in the search space, and they fluctuate around the best solution using sine and cosine functions. Therefore, the simple variation of sine and cosine function values is used to achieve the final optimal solution. The positions of the random solutions are updated using the following equations:

$$P_i^{t+1} = \begin{cases} P_i^t + r_1 * sin(r_2) * |r_3 R_i^t - P_i^t|, \ r_4 < 0.5 \\ P_i^t + r_1 * cos(r_2) * |r_3 R_i^t - P_i^t|, \ r_4 \geq 0.5 \end{cases} \qquad \textit{Eq. 25}$$

Where the current iteration is denoted as t, R_i^t is the i-th dimension destination point positioning, and P_i^t is the i-th dimension location of the main approach, at iteration t. The random numbers are r_1, r_2, r_3, and r_4 . r_1 and r_3 have a homogenous distribution between 0 and 2. Both r2 and r4 have a homogenous distribution between 0 and 2. r2 and r4 both follow a uniform distribution between 0 and 2 and a homogenous distribution between 0 and 1.

In Eq. 25, the algorithm's global research and local improvement capacities are collaboratively guided by $r_1 * \sin(r_2)$ or $r_1 * \cos(r_2)$. The algorithm does a global exploration search when the result of $r_1 * \sin(r_2)$ or $r_1 * \cos(r_2)$ is higher than 1 or less than -1. The algorithm does a local development search when the value of $r_1 * \sin(r_2)$ or $r_1 * \cos(r_2)$ is within the range of [-1 1]. Within the range of [-1 1], the value of $\sin(r_2)$ or $\cos(r_2)$. As a result, the control parameter r_1 is critical in global exploration, it is in charge of the algorithm's shift from global exploration to local development. The control parameter r 1 in the original algorithm uses a linear decreasing technique to direct the process from global exploration to local development, and it is adaptively changed over the course of iterations, as follows:

$$r_1 = a\left(1 - \frac{t}{T}\right) \qquad \textit{Eq. 26}$$

Where a is a constant, t characterizes the existing repetition, and T is the total amount of repetitions. SCA has been used to identify the global best solution to both constraint and unconstrained optimization issues.

XII. Simulation Results & Discussion

This section presents and discusses the simulation results of DOA estimation using ML-COA, ML-SCA, MUSIC and CAPON.

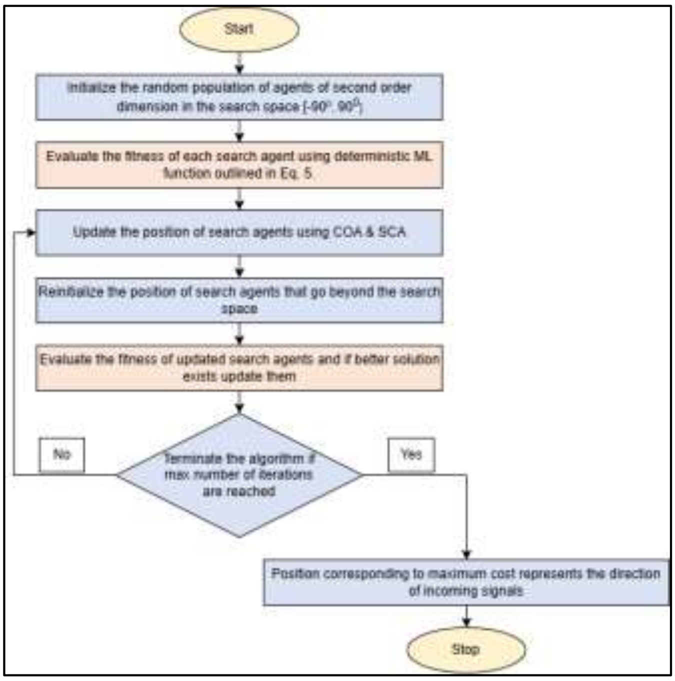

Fig. 2 Implementation of COA and SCA for estimating the direction of signals

Using 100 Monte Carlo at a 10-element ULA, two narrow-band plane waves with arrival angles of 35° and 38° are taken into consideration for MATLAB software simulation. The uncorrelated BPSK signals are simulated in the virtual environment since the model is deterministic. Regarding the two traditional algorithms, MUSIC and CAPON, the peaks of the pseudospectrum indicate the direction of incoming signals and are in the [-90°, 90°] range. Since 100 Monte Carlo runs are taken into consideration to determine the optimal value of the direction of incoming signals, COA and SCA are stochastic algorithms. Table 1 lists the criteria that COA and SCA took into consideration.

Table 1 Parameters considered for COA and SCA

Sr. No.	**Algorithm Configurations**

1	***ML- Algorithm***	***Population Size***	***Parameters***
2	COA	30	Constant (b) = 1
3	SCA	30	Controlling (r_1) = [0, 2]

Since ML-COA and ML-SCA are iterative algorithms, their effectiveness is also evaluated in terms of the rate of convergence. The performance of all four methods listed is evaluated using RMSE and PR criteria.

XIII. ROOT MEAN SQUARE ERROR

The difference between the actual signal and the determined signal heading is represented by the root mean square error, which can be defined as follows:

$$RMSE = \sqrt{\frac{1}{N_n N_{runs}} \sum_{x=1}^{N_{runs}} \sum_{y=1}^{N_n} \left[\hat{\theta}_y(x) - \theta_y\right]^2} \qquad Eq.\ 27$$

Where N_{runs} represents the Monte Carlo runs, N_n denotes the total number of sources, $\hat{\theta}_y(x)$ represents the y^{th} direction of the signal in the x^{th} run and θ_y denotes the true direction of the y^{th} signal.

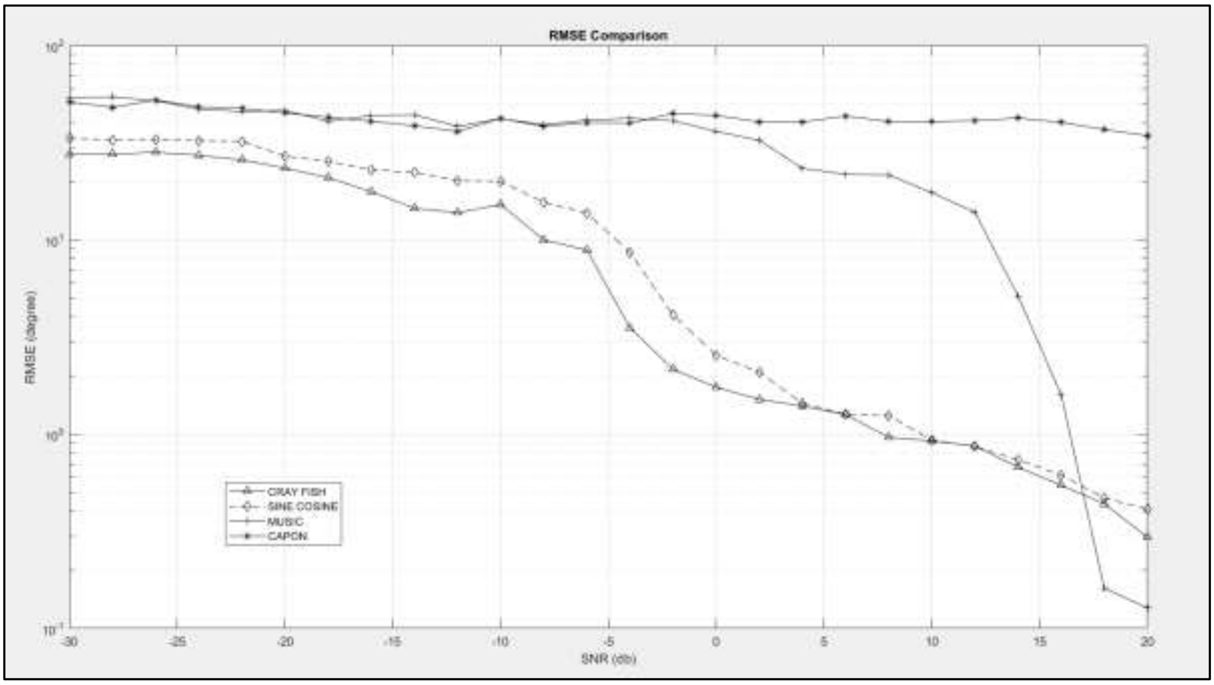

Fig. 3 RMSE plot of DOA estimation w.r.t SNR for MUSIC, CAPON, ML-COA and ML-SCA

Fig. 3 illustrates the variation of RMSE for CAPON, MUSIC, ML-COA and ML-SCA with respect to SNR in the range [-30, 20] dB. The result shows that the ML-COA algorithm presents the best results with respect to ML-SCA and conventional algorithms till 16 dB SNR while at SNR higher than 16 dB MUSIC algorithm outperforms all three algorithms. Therefore, the ML-COA algorithm produces the best result and can be utilized for estimating the direction of signals in a low SNR environment.

XIV. PROBABILITY OF RESOLUTION

The capacity of the algorithm to resolve sources that are closely spaced is known as the probability of resolution. It is crucial to assess the algorithm's resolving ability based on the multi-source estimation criteria, which states that sources are considered determined if the difference between the estimated and true angles of signals is less than half of the variance between the two signals.

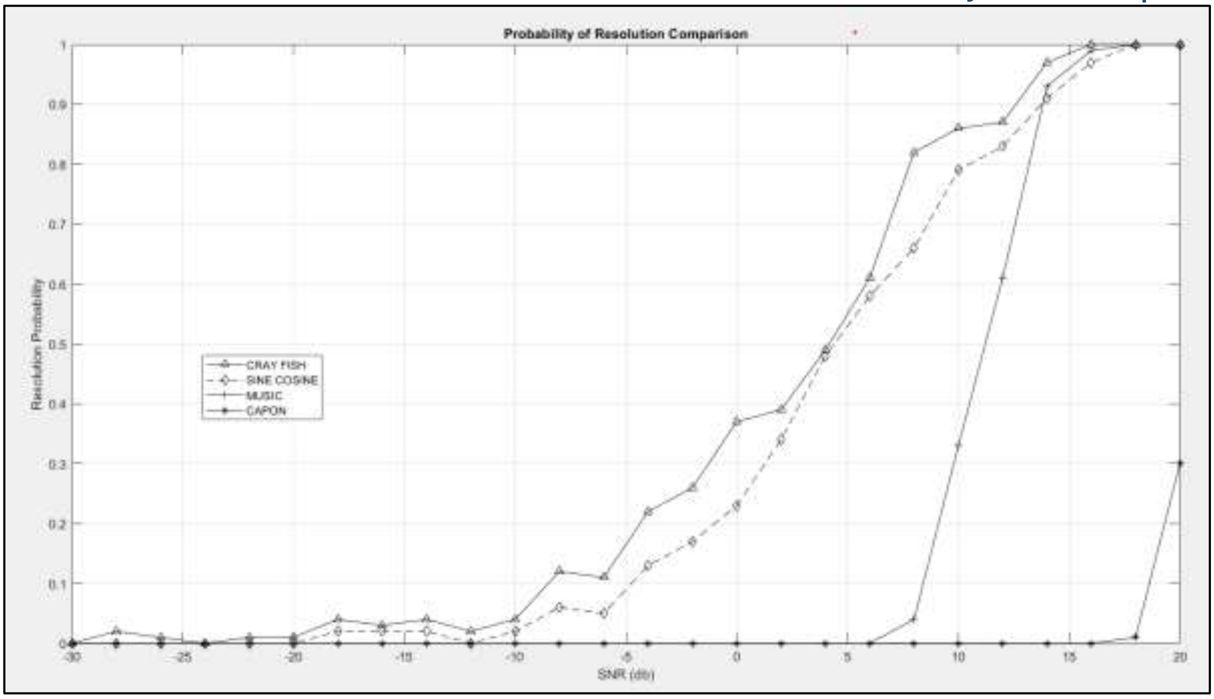

Fig. 4 Demonstrates the variation of PR with respect to SNR for CAPON, MUSIC, ML-COA and ML-SCA.

The result shows that the ML-COA algorithm presents the best results and at 16 dB completely resolves the two signals while MUSIC and ML-SCA completely resolve the two signals at 18 dB and 20 dB. CAPON didn't resolve the two signals till 20 dB. With these results, we can conclude that the ML-COA algorithm can be used in situations where the two signals have narrow angular separation.

XV. BOXPLOT

The rate of convergence is crucial in DOA estimation since adaptive methods are used to align the beam in the intended user's direction once the signal direction has been estimated. The boxplot for ML-COA and ML-SCA for 100 Monte-Carlo runs is displayed. The results show that, in contrast to ML-SCA, ML-COA correctly determines the direction of closely spaced signals.

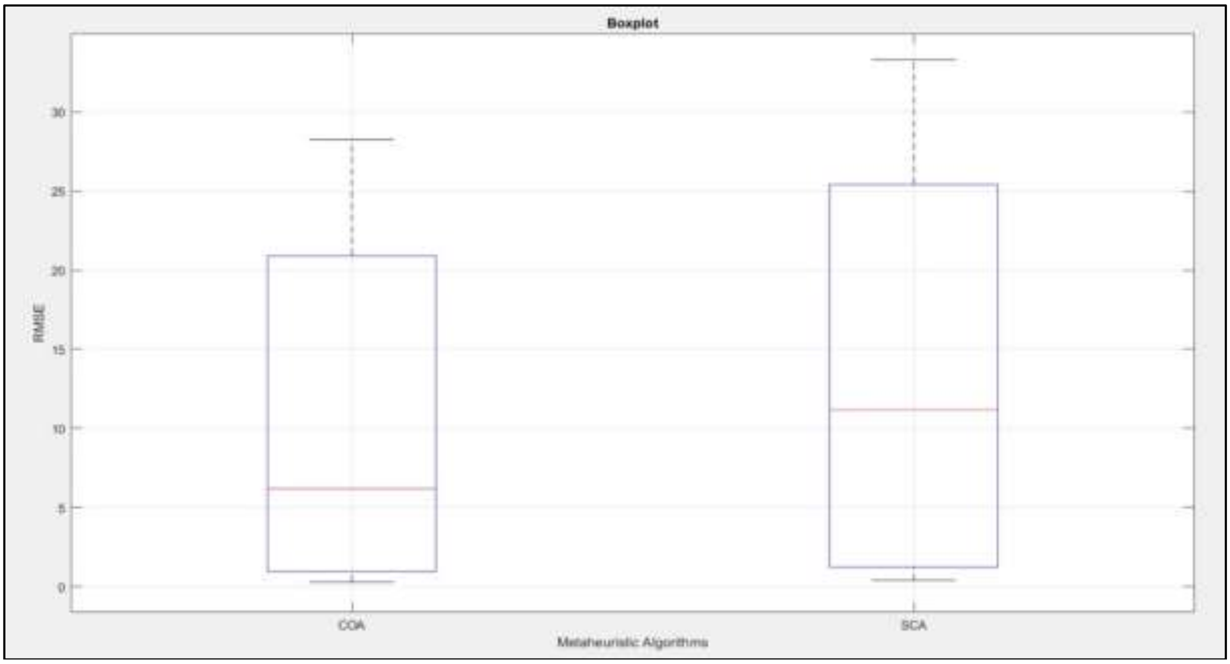

Fig. 5 Boxplot of ML-COA and ML-SCA

I. CONCLUSION

This chapter proposes a COA algorithm that optimizes the deterministic ML function to estimate the direction of incoming signals toward a linear array. The algorithm's performance is examined in terms of RMSE and PR and contrasted with that of the ML-SCA, MUSIC, and CAPON algorithms. The outcome demonstrates that ML-COA performs better than other methods in low SNR environments, yields the best results, and correctly predicts the direction of signals with small angular separation. The performance of the suggested algorithm is also examined using the fitness value distribution, which is an essential measurement for optimization algorithms. The outcome demonstrates that ML-COA produces trustworthy conclusions and converges significantly earlier than ML-SCA.

Future research could investigate the suggested metaheuristic approach for DOA estimation in a variety of channel environments and array configurations. Other challenging issues in the domains of science and engineering can also be resolved with the help of the suggested COA algorithm.

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