

A novel ML DOA estimation algorithm for array signal processing

Pengfei Shi¹, Xinnan Fan^{1,a}, Jianjun Ni¹ and Dewei Yang²

¹College of IOT Engineering, Hohai University, 213022 Changzhou, China

²Nanjing Hydraulic Research Institute, Nanjing, 210029 China

Abstract. A novel algorithm for finding the optimal solution of nonlinear function in maximum likelihood DOA estimation is proposed to reduce the calculation in multi-dimensional nonlinear search of the estimation. In the proposed method, firstly, the mode of population initialization mode is modified to improve the stability of population evolution. Secondly, the crossover operator is also improved to enlarge the range of new generated individual. Thirdly, parameters adaptive adjustment strategy is designed to accelerate convergence. The simulation shows that the proposed algorithm can greatly reduce the calculation time.

1 Introduction

Direction of arrival (DOA) estimation is an important process in array signal processing[1]. The DOA estimation algorithms are mainly divided into three types[2]: conventional beamforming (CBF), subspace-based(SB) and maximum likelihood (ML). However, CBF is limited by the array physical aperture. It cannot distinguish between two spatial targets within a beam width[3]. SB cannot solve the computational complexity problem well when the number of sensors is large[4]. ML DOA estimation algorithm is a representative and practical estimation algorithm of DOA estimation theory. It can achieve a good estimation performance, especially in asymptotic estimation[5]. The ML DOA estimation has attracted more and more attention from researchers.

However, the ML DOA estimation contains a multi-dimensional nonlinear function, which will lead to a high computational cost. Researchers attempted to use intelligent algorithms based on bionics to solve the multi-dimensional nonlinear searching problem in ML DOA estimation. Such as the differential evolution (DE) algorithm[6], the artificial bee colony (ABC) algorithm[7], and the particle swarm optimization (PSO) algorithm[8].

In this paper, a fast algorithm of ML DOA estimation based on bee evolutionary genetic algorithm (BEGA) is proposed to optimize ML DOA estimation. BEGA introduces some excellent evolutionism of bee to emphasize the importance of the optimum individual in population evolution. It can converge to global optimal solution quickly[9].

The proposed algorithm mainly improves BEGA from three parts: population initialization, crossover operator and adaptive adjustment of parameters. Simulation results show that the algorithm not only keeps the estimated

accuracy of original ML DOA estimation algorithm, but also significantly simplifies the calculation.

2 The proposed algorithm

2.1 Signal Model of Array

Assuming that a uniform linear array is made up of M elements and its element gap is d. The sketch of array receiving signal from far field source is as shown in Figure 1.

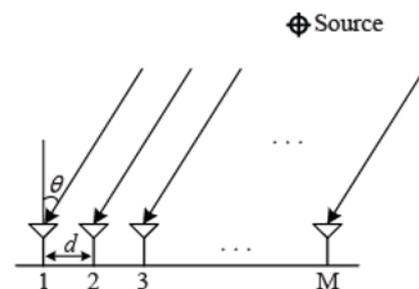


Figure 1. Sketch of array receiving signal

The ML estimation about parameter θ is calculated as Equation (1).

$$\hat{\Theta} = \min_{\theta} \left\{ \text{tr} \left\{ \mathbf{P}_A^+ \hat{\mathbf{R}} \right\} \right\} = \max_{\theta} \left\{ \text{tr} \left\{ \mathbf{P}_A \hat{\mathbf{R}} \right\} \right\} \quad (1)$$

Where $\Theta = [\theta_1 \ \theta_2 \ \dots \ \theta_p]^T$, \mathbf{P}_A is projection of matrix \mathbf{A} , $\text{tr}\{\bullet\}$ is trace of a matrix, \mathbf{P}_A^+ is orthogonal projection matrix of matrix \mathbf{A} and \mathbf{A}^+ is pseudo-inverse of matrix \mathbf{A} .

^a Corresponding author: fanxn@hhuc.edu.cn

2.2 Algorithm Flow

Figure 2 shows the flow of proposed algorithm. Firstly, it calculates sample covariance matrix of array received data. Then it carries out the ML DOA estimation with sample covariance matrix. In order to speed up the search of nonlinear global optimum solution while doing ML DOA estimation, this paper optimizes the search with the aid of improved BEGA. According to the character of ML DOA estimation, the algorithm is improved in three parts: population initialization method, crossover operator and adaptive adjustment of parameters.

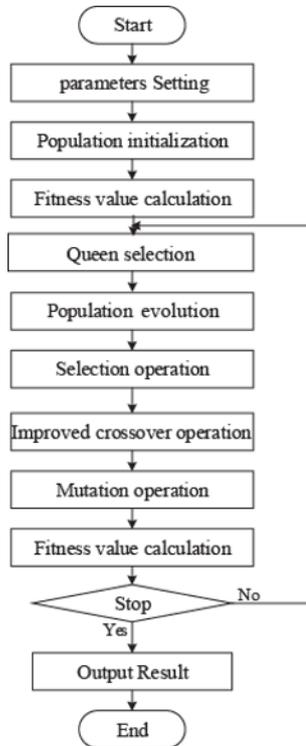


Figure 2. A fast algorithm for ML DOA Estimation

2.3 Population Initialization

Population initialization is the first step for population evolution and it provides an initial guess. Then, these initially guessed solutions will be iteratively improved in the course of the optimization process until a stopping criterion is met[10]. Generally, population initialization can affect the convergence speed and also the quality of the final solution[11]. Good initial population facilitates a GA's convergence to good solutions while poor initial population can hinder the convergence.

The random initialization is a default method of population generation. It employs pseudo-random number generator(PRNG) to produce the initial population[12]. The rationale behind this is that the PRNG can generate uniformly distributed samples and thus a population initialized using PRNG tends to cover promising regions which contains global optima or good local optima of the search space. Since the population size is always limited, the chance for a population to cover promising regions of the search space decreases as increasing the dimension of the search space. So,

increasing the chance for a population to cover promising region of the search space is important.

Thus, in order to improve the traditional random initialization, solution space is divided into some subspace, and then the PRNG is used to get random result in each subspace as the initial population. It can be expressed with Equation (2).

$$p[i] = [r(0,1) + (i-1)] \times \frac{180^\circ}{l} + (-90), i = 1, \dots, l \quad (2)$$

Where $r(0, 1)$ is random number in interval $[0, 1]$, $p[i]$ is the i th individual of initial population and l is the size of population.

2.4 Crossover Operator

In BEGA, the optimum individual is chosen as the queen to operate the crossover with all the individuals in population. The range of new individual obtained by crossover operator represents the excavation ability of the crossover operator does with the optimum individual. Thus, this paper utilizes the improved crossover operator to expand the range of new individual to both sides of the queen. First, the crossover range is expanded to $[Q-\Delta, Q+\Delta]$, and then PRNG is used to achieve crossover result. It can take fully advantage of the information in queen. Advanced crossover operator can be expressed with Equation (3).

$$p_n[i] = Q + r(-1,1) \times |Q - p_s[i]| \quad (3)$$

Where Q is the queen in each generation, $p_n[i]$ is i th new individual obtained after crossover, $p_s[i]$ is i th individual selected to crossover and $r(-1, 1)$ is random number in interval $[-1, 1]$.

2.5 Adaptive Adjustment of Parameters

The performance of BEGA is determined by the balance between depth and breadth search in searching space. Adjusting the parameters to keep the search breadth as large as possible with the precision of solution meeting the requirement. Parameters affect evolution of BEGA are mutation probability P_m , random individual range R_s and mutation interrupt range R_m . P_m is used to control the probability of mutation occurrence. R_m is used to control the range of mutation, means the range of individual x after mutation is $[x-R_m, x+R_m]$. Mutation operation is an auxiliary method of new individual generations and it determines ability of local search.

For ML DOA estimation, mutation operation not only controls the search range, but also determines the search precision. Increasing P_m and reducing R_m can shrink local search range and increase the depth of local search. It means that algorithm can obtain more possible solutions in unit range. R_s is used to control the range of random individual generate around near optimal solution. Increasing R_s can keep the waiting population at a high diversity. Thus it can avoid losing useful genetic

information and improve the global convergence of algorithm.

In order to balance depth and breadth search and obtain the co-evolution of parameters and population, this paper adopts adaptive adjustment strategy as follows:

$$\left[\begin{array}{l} \text{mutate_rate} = 0.5 \\ \text{selection_range} = 0.5 \\ \text{mutate_range} = \frac{\text{selection_range}}{10} \end{array} \right], \text{std}(fvalue) < \text{std}(fvalue_last)$$

$$\left[\begin{array}{l} \text{mutate_rate} = 0.1 \\ \text{selection_range} = 1 \\ \text{mutate_range} = \frac{\text{selection_range}}{2} \end{array} \right], \text{std}(fvalue) \geq \text{std}(fvalue_last)$$

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Where $fvalue$ is fitness value sets of current population, $fvalue_last$ is fitness value sets of previous population and $std(\bullet)$ is standard deviation. Standard deviation value reflects the discreteness of datasets. If fitness value sets meet $std(fvalue) < std(fvalue_last)$, it means that the evolution has a convergence trend. At the same time, increasing P_m and decreasing R_s and R_m can enhance the impact of local search in population evolution and expand the depth of local search. It is aimed to excavate high precision solution in the convergence direction of population evolution. Instead, $std(fvalue) \geq std(fvalue_last)$ means that the evolution has a divergency trend. Decreasing P_m and increasing R_s and R_m can slack impact of local search and expand the breadth of global search. It can make algorithm jump out and avoid convergence to near optimal solution.

3 Simulation and Analysis

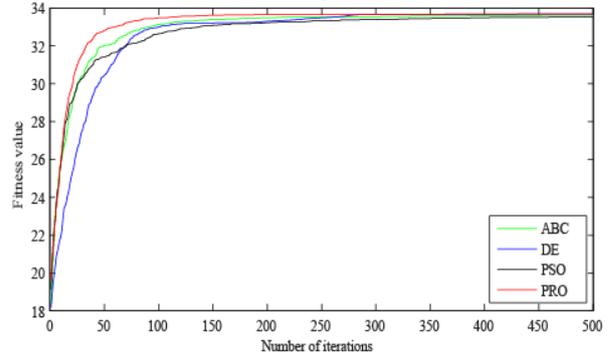
In this section, we demonstrate the simulation results of the proposed algorithm(PRO). Then we compare the proposed method with ABC, DE, and PSO search methods. For the sample data, the receiver array is supposed to be a 16 sensor uniform linear array and 500 data snapshots are used. Convergence rate and speed are important factors to evaluate the efficiency of an algorithm. The setting parameters of the proposed algorithm are shown in Table 1.

Table 1. Setting parameters of proposed algorithm

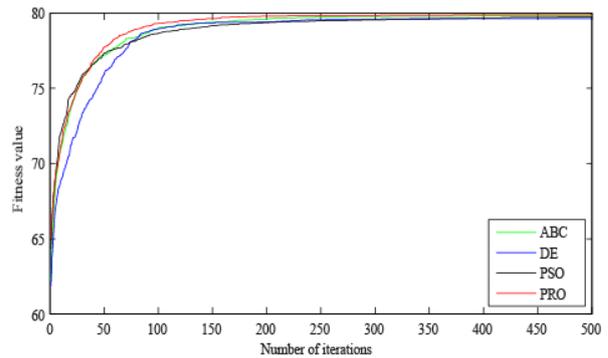
Parameters	Value	Remarks
l	10	population size
G_{max}	500	maximum generation
P_m	0.01	mutation probability
R_s	1.0	random individual range

R_m	0.5	mutation interrupt range
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In order to demonstrate the accuracy and reliability, the estimation process curves are obtained over an average of 500 times of the experiment. The curves are the estimation value found by the algorithm for each iteration versus the increasing number of iteration.



(a) SNR = 0dB



(b) SNR = -10dB

Figure 3. Fitness values of DE, ABC, PSO and PRO with two signal sources

Figure 3 shows the convergence properties of DE[6], ABC[7], PSO[8] and proposed algorithm with SNR = 0dB and SNR = -10dB respectively. As we see in the figure, the proposed algorithm reaches the final value faster than other algorithms no matter SNR = 0dB or SNR = -10dB. It means that the proposed algorithm can always converge to the optimal solution with fewer steps than other algorithms, which influence the computational load of the algorithm.

4 Conclusion

This paper improves the BEGA to optimize ML DOA estimation which can be used in the large amount of calculation problem of the nonlinear global search in ML DOA estimation. In the proposed method, the population initialization is modified to improve the stability of population evolution and the crossover operator is also improved to enlarge the range of new generated individual. At last, parameters adaptive adjustment strategy is designed to accelerate the convergence. All the improvements are verified to be effective according to simulation results. The simulation shows that the proposed algorithm can reduce the calculation time greatly.

Acknowledgments

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