Application of PSO-GA&CGA in Sea-Clutter Doppler Spectrum Modeling

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***Abstract*—In the field of sea clutter research, the key of sea targets recognition and detection is that accuracy estimated parameters of the Doppler Spectrum modeling through the optimal solution search algorithm. Our work provides two ways to improve heuristic search algorithm. One is CGA(Continues-mutation Genetic Algorithm) that cloud prevent Hamming Cliff, which is considered as GA's inherent issue. The other is that the PSO-GA (Particle Swarm Optimization and Genetic Algorithm) and PSO-CGA (Particle Swarm Optimization and Continues-mutation Genetic Algorithm) obtained by combining algorithms, which can take advantages of the original methods and increase the individuals utilization rate. Both these method can reduce the error of the obtained results without increase solving time. In addition, we also proposes a new evaluation method of the heuristic search algorithm to efficiency measure algorithms.**

***Index Terms*—Sea Clutter, Heuristic search algorithm, Genetic Algorithm, Particle Swarm Optimization, Continues-mutation Genetic Algorithm**

I. Introduction

In the ocean background, the interference of sea clutter is inevitable in radar target detection and recognition[1]. Therefore, the interference of sea clutter need to be eliminated by studying the property. The Doppler characteristic is one of the most important characteristics of sea clutter, which can be described by Doppler spectrum.

The model of sea clutter Doppler spectrum is an empirical model, which needs to be optimized. Most of the Doppler spectral models of sea clutter are based on Gaussian spectral models, and the interpretation of each Gaussian component is different. In [2], it is considered that the Doppler frequency shift is composed of three kinds of scattering frequency shifts, i.e. Bragg scattering, Whitecap scattering and Spike scattering. The three kinds of components are separately represented by Gaussian model. In [3], the Doppler spectrum can be divided into two parts: one is the Bragg scattering component, the other is the combination of the Whitecap scattering and Spike scattering. The Doppler spectrum is also described by the composite Gaussian model. A time-varying Doppler spectrum model based on composite Gaussian distribution is proposed by [4]. So far, most of the work about the Doppler spectrum of sea clutter is to model the composite Gaussian model of the power spectrum, and the parameters in the model need to be optimized by the optimal solution search algorithm. LM (Levenberg-Marquardt) algorithm is used to estimate the parameters of Doppler spectrum model in [5], but LM algorithm is easy to fall into the local optimum when solving the high dimension. Powell algorithm is used to estimate the parameters of the composite Gaussian model in [2]. PSO Particle swarm optimization is used to search for the optimal solution in [4]. PSO has a fast iteration speed, but it is sensitive to the initial value and the optimization process is not stable.

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For the modeling of sea clutter Doppler spectrum model, we propose two improved heuristic search methods to optimize the solution. Compared with other methods, our method has a better performance in fitting process. For the purpose of this article:

1. Explore the shortcomings of genetic algorithm and particle swarm optimization algorithm, and improve the algorithm.

2. Apply the proposed method to model the Doppler spectrum model of sea clutter.

3. A new evaluation method of heuristic population algorithm is proposed to verify the effectiveness of our algorithm.

About the arrangement of the article, in the second section, we will introduce the Doppler spectrum model that we used in, the baseline optimization method and the improved method. In the third section, we will further analyze the shortcomings of common algorithms and how the new method is improved, and at the same time, we will compare the widely used methods with our method in new evaluation standard.

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II. Doppler spectrum model and parameter estimation of sea clutter

According to the formation mechanism of the sea clutter Doppler spectrum, based on different observation time, the sea clutter Doppler spectrum shows different shape and non-stationary[6-8]. Therefore, the modeling of sea clutter Doppler spectrum can be divided into two cases. One is to model the average Doppler spectrum, that is, the average characteristics of the sea clutter spectrum for a long time (usually greater than the gravity wave period in second level). The representative models are Lee's model and Walker's model[9-11]. One is for short-time dynamic Doppler spectrum modeling(usually less than the period of gravity wave, more than the decorrelation time of white wave scattering and broken scattering). The representative is Ward's model. Due to the complexity of the form and parameter estimation of Lee's model, it is difficult to apply it in practice. In this work, Walker's model is mainly used to model the Doppler spectrum of HH polarization sea-clutter data in P-band and S-band.

A. Walker Model

Walker model[2,12] assumes that the spectral components of three different scattering mechanisms are described by Gaussian spectral line function. For HH polarization, the spectral model is in the form of:

$$\begin{aligned} S_{HH}(f) =& B_H exp[-\frac{(f-f_B)^2}{w_B^2} + W exp[-\frac{(f-f_G)^2}{w_W^2}] \\ &+ S xp[-\frac{(f-f_G)^2}{w_S^2}] \end{aligned} \quad (1)$$

For VV polarization, the spectral model is as follows:

$$S_{HH}(f) = B_V exp[-\frac{(f-f_B)^2}{w_B^2} + W exp[-\frac{(f-f_G)^2}{w_W^2}] \quad (2)$$

where f is the frequency. Respectively, B_H and W are the coefficients of Bragg scattering and whitecap scattering. f_B,f_G corresponding to the Bragg resonant wave and gravity wave phase speeds. w_B, w_W, w_S are the Doppler spectral width of Bragg, whitecap and spike scattering respectively. Both polarisations contain identical non-Bragg whitecap terms, but the horizontal polarisation includes 'spike' term.

B. Solving Model Parameters

To model the Doppler spectrum of sea clutter, it is necessary to optimize the model parameters. For the Walker's model with HH polarization, there are eight parameters, i.e. B, W, S, f_B, f_G. W_B, w_W and w_S need to be searched and solved. For the optimal solution search, we will introduce several algorithms as baseline, including L-M algorithm, PSO, GA (Genetic Algorithm).

*a) **Levenberg-Marquardt:*** LM algorithm is one of the commonly used optimal solution search algorithms. It combines the advantages of Gauss-Newton method and gradient descent method, and better the disadvantages of them[13,14].

The iterative formula of Gauss Newton method is as follows:

$$x_{k+1} = x_k - [J_k^T J_k]^{-1} J_k^T g_k \quad (3)$$

J is the Jacobian matrix of the loss function.

In LM algorithm, damping factor μ is applied to adjust the characteristics of the algorithm. The iterative formula is:

$$x_{k+1} = x_k - [J_k^T J_k + \mu I]^{-1} J_k^T g_k \quad (4)$$

Where μ is a positive parameter, which can ensure the positive determination of coefficient matrix, so as to ensure the descent direction of iteration. When the μ is bigger, LM algorithm degenerates into gradient descent method:

$$x_{k+1} = x_k - \frac{1}{\mu} J_k^T g_k \quad (5)$$

For a small μ, the algorithm degenerates to Gauss Newton algorithm, which makes it converge quickly when it is close to the best solution.

LM algorithm is easy to fall into local optimum point in the process of searching the optimal solution, especially in the condition of high dimension.

*b) **PSO:*** PSO[15,16] is a heuristic optimal solution search algorithm. Particle swarm optimization algorithm uses particle to represent each solution. Every particle has two attributes: velocity V and position X. Each particle searches for the optimal solution separately in the search space. Records it as the current optimal individuals, P_i, and shares the optimal individuals with other particles of the whole particle swarm to find the global optimal, P_g. Each particle in the particle swarm adjusts its moving speed and position according to its own individual extreme value and the current global optimal solution.

Where the iterative formula of V and X is as follows:

$$\begin{aligned} V_i = \omega V_I + c_p rand(0,1)(P_i - X_i) \\ + c_g rand(0,1)(P_g - X_i) \end{aligned} \quad (6)$$

$$X_i = X_i + V_i \quad (7)$$

ω is the inertia factor, an acceleration factor. The individual speed direction is determined by three factors, one is the current speed direction, and the other two are the individual optimal direction and the group optimal direction.

*c) **Genetic Algorithm:*** GA [17] is a heuristic search through chromosomal cross mutation. After each iteration, the individuals with high fitness is retained, and other individuals are cross-matched and mutated with a certain probability. The genetic algorithm uses binary coding to determine the location of the cross and mutation, so there is a issue that the adjacent points has large distance, which called Hanming cliff.

*d) **Continues-mutation Genetic Algorithm:*** Because the binary coding cross mutation method used in Genetic Algorithm , there will be a problem of search dilemma. In order to explore and try to solve this problem, we improve the mutation method to alleviate the search dilemma caused by Hanming cliff.

The improved mutation method we have proposed is to add a continuous mutation factor to the GA algorithm mutation phase. It can be expressed as follows:

$$Discrete \quad mutation : A = X \sim U(a,b) \quad (8)$$

$$Continues \quad mutation: A = A + rAs.t.r \sim N(0, \sigma^2) \quad (9)$$

Among them, A is the value of mutation individuals. Continuous mutation is add a perturbation factor to the original value. This method also conforms to the law of natural mutation.In this article, we take σ as 1. For individuals with better fitness, continuous mutation is used for local search; for the poor fitness individuals, discrete mutation was used for global search.

*e) **PSO-GA**:* PSO and GA are used to optimize the model parameters in cascade way. Through this method, it will combine the advantages of the two methods to improve the optimization process.

The PSO has undergone numerous advantages at guaranteeing convergence, computing fast and simple to iterate. Although the local search ability is strong, the search range is limited. The population diversity will become worse during the iteration process. it is easy to fall into a local optimum. Otherwise, the PSO algorithm is sensitive to the initial value of the solution. If the initial value is far away from the actual value of the model, the optimization result will be worse. Therefore, before using the PSO algorithm to optimize, it's necessary to observe the data to obtain a rough solution range to initialize the solution parameters, which is extremely inconvenient to apply. On the other hand, the GA algorithm uses the Hamming distance measure when crossing and mutating. Although the population diversity is strong, due to the existence of the Hamming cliff, the convergence is slow. Therefore, the combination of the two methods can improve the parameter optimization.

The PSO-GA pseudo code can be expressed as $ALGORITHM$ 1:

Algorithm 1 PSO-GA

Input: Sea Clutter Doppler Spectrum Pxx; Doppler Spectrum model M; Parameter number of Doppler Spectrum model D;PSO group number G_{PSO}; GA group number G_{GA};Iteration number I_{PSO}, I_{GA}.

Output: Model Parameter W

c_g, c_p, ω, V /*Initialize PSO parameter*/
$W_{PSO} = Uniformrand(G_{PSO}, D) = [w_1; ...; w_{G_{PSO}}]$
for $i = 0$ to I_{PSO} **do**
  $W_{PSO} = PSO(W_{PSO}, c_g, c_p, \omega, V)$
  $W_{GA} = [W_{PSO}; Uniformrand(G_{GA} - GPSO, D)] = [W_{PSO}; w_{G_{PSO}+1}; ...; w_{G_{GA}}]$/*Initialize GA parameter*/
  for $j = 0$ to I_{GA} **do**
    $W_{GA} = GA(W_{GA})$
  end for
  $fitness = \frac{1}{G_{GA}}(Pxx - M(W_{GA}))^2$
  $W_{GA}[Sort(fitness)]$
  $W_{PSO} = [W_{PSO}[1 : \frac{G_{PSO}}{2}; W_{GA}[1 : \frac{G_{PSO}2}{]}$
end for
$fitness = \frac{1}{G_{PSO}}(Pxx - M(W_{PSO}))^2$
$W_{PSO}[Sort(fitness)]; W = Best(W_{PSO})$
return W

After the PSO search, use the PSO optimization results as GA initial solution. After the GA search, replace the poor fitness individuals in the PSO by better fitness individuals in GA. In this way, the advantages of the PSO algorithm and GA algorithm can be retained.

III. Experiment

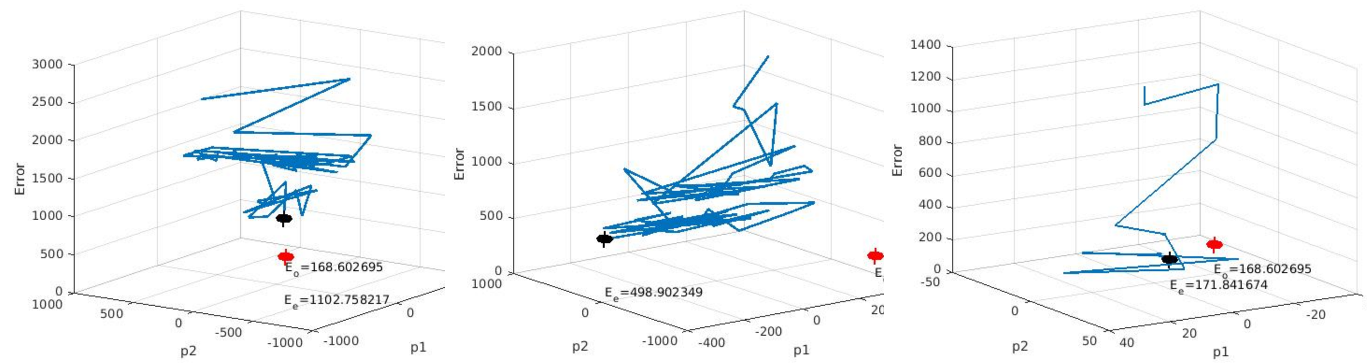
In the experimental part, we will use the methods which been proposed to compare with PSO, GA and LM on the parameter estimation of the Walker's power spectrum models of sea clutter. Analyze all the optimization methods from multiple angles. Evaluation the effectiveness, advantages and disadvantages. We will analyzes the PSO-GA model in first subsection, compares the five algorithms from the perspective of the solution path in second subsection. Analyzes the algorithms from the perspective of new evaluation method, EPTS, in the third subsection. When visualizing the search process, due to there are too many model parameters, we use the t-SNE algorithm to perform dimensionality reduction on the parameters to visualize the search process. For visual comparison of search results, we compare the observation result with the search result.

A. Model Analysis

In the random initialization process, the number of populations affects the diversity of the population, determines the search range and the speed of the solution. Therefore, this subsection will analyze from the perspective of the impact of population number on the model. PSO-GA can find the optimal solution with fewer population numbers.

When the number of GA populations are 0, the GA algorithm does not work, and PSO-GA is degraded into PSO algorithm. As shown in Fig.1. (a),(b), GA uses the search results that searched by PSO. At this time PSO -GA has a certain global search capability. When it is trapped in a local optimum, it could take the advantages of genetic algorithms to perform a global search, jump out of the local optimum, and further iterate to the global optimum. With the G_{GA} increase, the search capability of PSO-GA is raised, and it is easier to jump out of the local best advantage and approach the optimal value of observation. As shown in Fig.1. (c), at that time, the advantages of the GA algorithm and the PSO algorithm could fully combination. Especially in the initial iteration period, it could quickly reach an ideal range. When the search dilemma is encountered in the later iterations, the genetic algorithm can search in a relatively large range. And at the same time, PSO can ensure that the results of each iteration are not too bad, so that the iteration results are getting closer to the global optimum.

Therefore, the PSO-GA algorithm can use the advantages of the PSO algorithm at the early stage of the iteration to make the error quickly decline. When the optimization is advanced, the advantages of the GA algorithm can be used to further reduce the error. Combined with two part that can be used in a small population for a better results. As shown in Fig.2.,



(a) $G_{PSO} = 30, G_{GA} = 10$ (b) $G_{PSO} = 30, G_{GA} = 20$ (c) $G_{PSO} = 30, G_{GA} = 50$

Fig. 1. The results of PSO-GA(Red point E_o is observertion result.Black point E_e is search result)

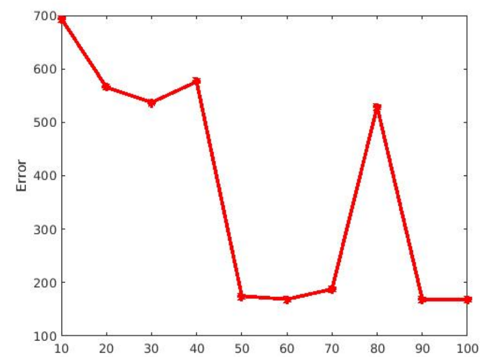


Fig. 2. Impacts of $G_{GA}(G_{PSO} = 30)$

when $G_{GA} \in [1.5G_{PSO}, 2G_{PSO}]$,the speed is faster and the error is smaller.

B. Optimizing Efficiency

PSO is faster in the initial iteration, but as the number of iteration times increases, the population diversity gradually worse, and falls into a local optimum. As shown in Fig.3, the figure shows the variance of each parameter of all populations after each iteration. From the figure, it can be seen that the variance of parameters in all populations is greatly reduced after iteration, and the diversity of the population is correspondingly reduced. It is difficult to jump out to achieve further optimization when fall in local optimum. Fig.4 (a) and Fig.4 (b) show the results of the iteration with the same random initialization method, the same population, and the same number of iterations. Two optimal solutions have a large gap, so the effect of the initialization value on the PSO is relatively large. The optimization process of PSO is not stable enough.

Fig.5. shows the GA optimization process. The cross and mutation in the GA optimization process uses binary coding method. Because of Hamming cliff issue, each iteration result will have a larger distance change. So GA has a stronger global search capabilities, but it is difficult to continue narrowing

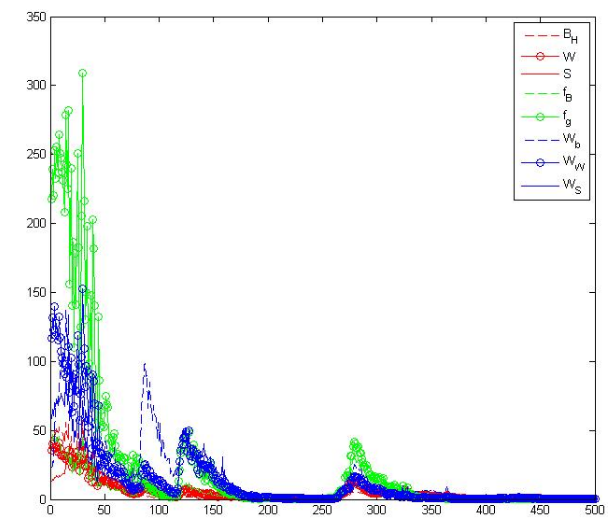
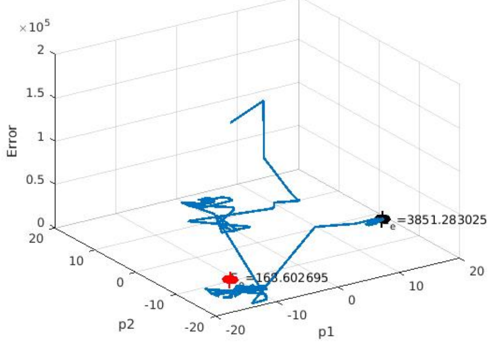


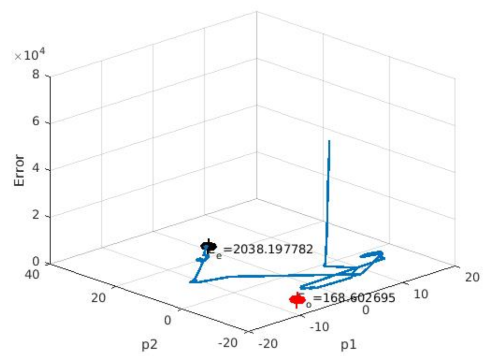
Fig. 3. Variance of particle in PSO

error. Respectively, two result are similar afteer different iteration times indicating that when the GA algorithm fall in a search dilemma, it is difficult to further reduce the error due to the Hamming cliff. Fig.6 (a) and Fig.6 (b) show the improved CGA algorithm in this paper. It can be seen from the figure that under the same number of iterations of CGA, better results can be obtained with a smaller number of populations. Compared with the original GA algorithm, CGA alleviates the problem of the Hanming cliff to a certain extent. During the search, discrete mutations continue to play the role of global search, while continuous mutations can search in the local area. The difficulty of binary coded search enables the algorithm to get out of the search dilemma. However, better search results can be obtained under a larger number of populations and iterations, and the individual utilization efficiency is still lower.

LM is a gradient algorithm, and its result is not affected by

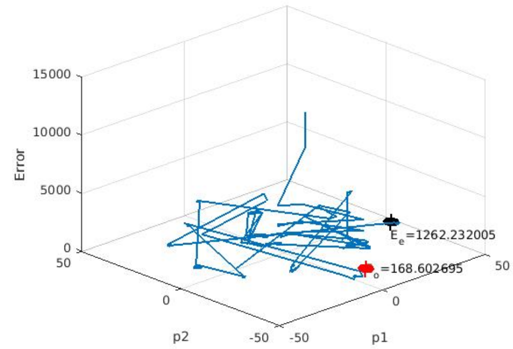


(a)

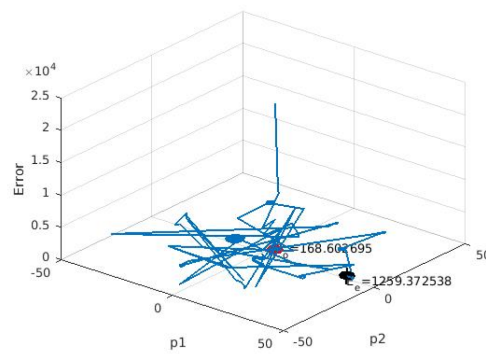


(b)

Fig. 4. Iteration results of the same random initialization, population number, and iteration number



(a) $iteration \quad number = 1000$



(b) $iteration \quad number = 3000$

Fig. 5. GA optimization process($G_{GA} = 300$)

the number of populations, but it is easy to fall into a local optimum when the solution dimension is too high, as shown in Fig.7 And the higher the dimension, the more complicated the gradient calculation process and the longer it takes.

In addition, we also integrated the CGA algorithm into the PSO algorithm and combined it into PSO-CGA. Fig.8 is the optimization process of PSO-CGA. We can find that there is small improvement between PSO-CGA and PSO-GA. This result shows that PSO-GA can better solve the problem of the Hanming Cliff that PSO-CGA can't make the algorithm in a huge improvement. Compared with PSO, GA, and CGA, the PSO-GA can obtain better search results through fewer populations. It can also better solve the problems that existing in PSO and GA, and haven't increase time cost. The running time and running error will be compared in the third subsection. In addition, PSO-GA is superior to the LM algorithm in both the running speed and search results.

C. Error Analysis

This subsection compares the five algorithms from three aspects: error, time, and population number. In order to make comparisons easier, we propose a new population algorithm evalutation method: $ETPS$ (Error-Time-Population size Standard). On this basis, we will make a reasonable comparison of the five algorithms.

ETPS can be expressed as follows:

$$EPTS(E,t,N) = \alpha E + \beta tanh(t) + \gamma tanh(N) \qquad (10)$$

Among $\alpha+\beta+\gamma = 1$, the ratio α,β and γ is used to balance the influence of the three factors on the algorithm, which is the proportional error. The calculation formula is as follows:

$$E = \frac{|p - \hat{p}|}{|p|} \qquad (11)$$

p is the actual sea clutter Doppler spectral value, and $\hat{p}$ is the Doppler model spectral value obtained by searching.t is the running time, N is the number of populations.

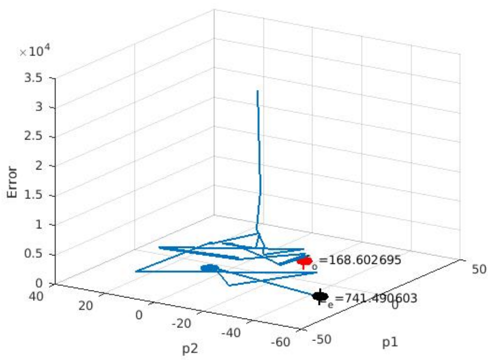
$$tanh(x) = \frac{sinh(x)}{cosh(x)} = \frac{e^x - e^{-x}}{e^x + e^{-x}} \qquad (12)$$

This function is to normalize the time and population to (0,1), so that it is measured in the same order of magnitude as the ratio error. Generally, the smaller the error, the shorter the time, the better the algorithm's effect, and the population number reflects the individual utilization rate during the search process. Under the same error condition at the same time, the smaller the population number, the higher the individual utilization rate, the smaller the memory space occupied by the algorithm, this standard is also very important in engineering applications. Therefore, the smaller the $ETPS$ value, the better the actual application effect. The experiments in this

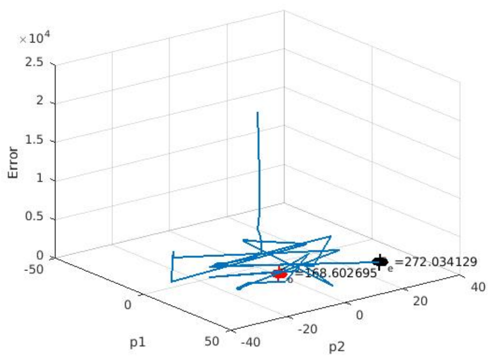
TABLE I

THE RESULTS OF ETPS BY USE DIFFERENT METHODS

	PSO(1000)	GA(5000)	CGA(5000)	LM	PSO-GA	PSO-CGA
P-band	1.28	0.98	0.76	-	0.73	**0.727**
S-band	1.13	0.81	0.60	-	0.57	**0.55**



(a) $iteration \quad number = 1000$



(b) $iteration \quad number = 3000$

Fig. 6. CGA optimization process($G_{GA} = 300$)

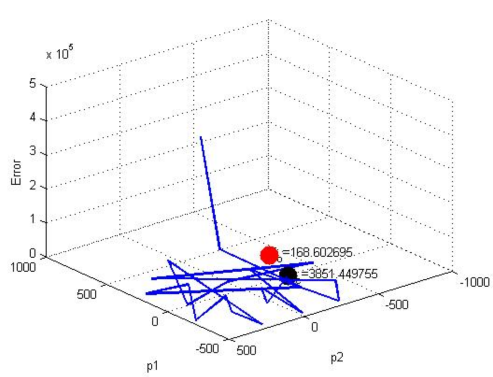
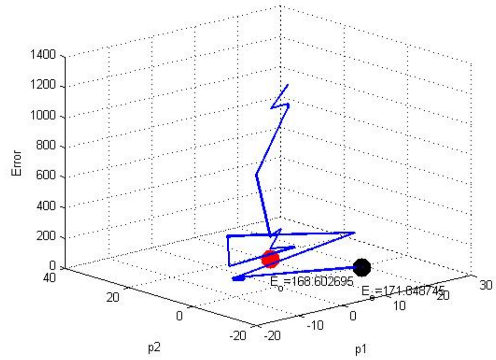
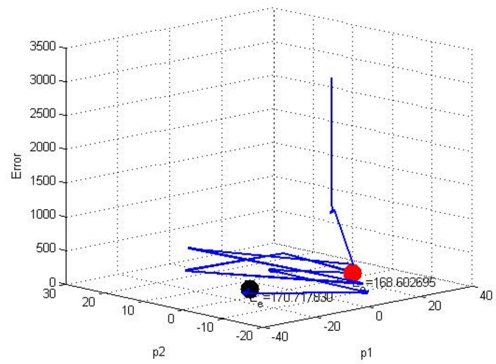


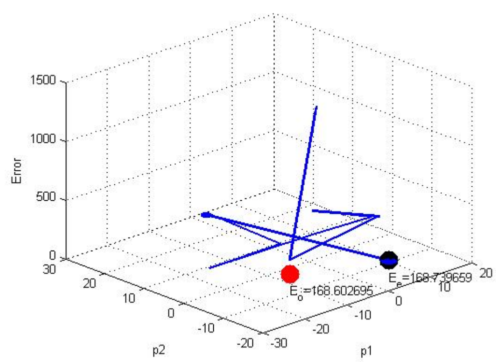
Fig. 7. The results of LM



(a) $G_{PSO} = 30, G_{GA} = 10$

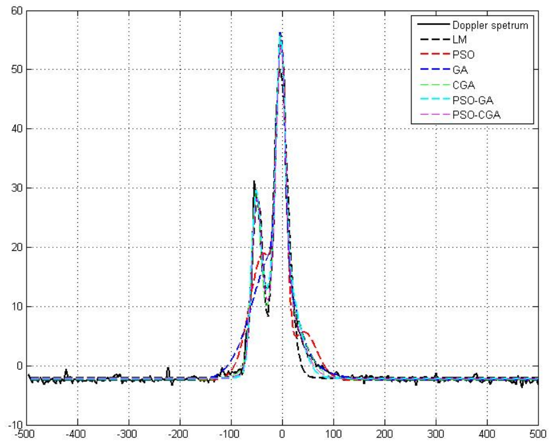


(b) $G_{PSO} = 30, G_{GA} = 20$

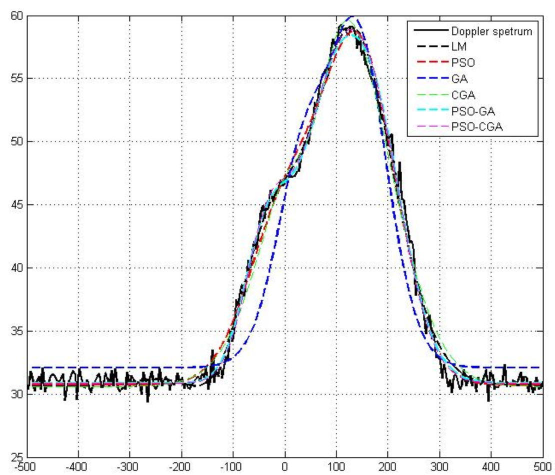


(c) $G_{PSO} = 30, G_{GA} = 50$

Fig. 8. PSO-CGA optimization process



(a) P-band



(b) S-band

Fig. 9. Doppler spectral model fitting results by using different methods

paper α,β and γ are taken as 0.4, 0.3, and 0.3 respectively. We are inclined to search the model parameters accurately, especially when the searching time has not changed distinctly. This also meets the needs of our practical application. After experiments, the ETPS results of the five different algorithms are shown in Table I. The ETPS value of PSO-CGA proposed in this paper is the smallest, but it is similar from PSO-GA, which also confirms our analysis results in former part. The change tendency of ETPS in both varieties was similar, but in terms of individual using rate and searching error, PSO-GA and PSO-CGA have more obvious outstanding. The LM algorithm is a gradient search algorithm, which cannot be compared by $ETPS$. Compared with the LM algorithm, our algorithm is better than the LM algorithm in both searching error and running time.The fitting result of five method in P-bans and S-band are shown in Fig.9.

IV. CONCLUSION

The Genetic algorithm and particle swarm algorithm have received considerable widely attention. Both of them have significance application in the search of hyper parameters of deep network models and the solution of model parameters . Especially in the widespread application of deep network models, manual adjustment of parameters will consume a lot of time and effort. The optimal solution algorithm will reduce a lot of time cost and reduce the dependence of artificial experience.This paper has given an account of and the reasons for the widespread use of an optimal solution algorithm in the field of sea clutter, which could be used in accurately model a variety of sea clutter models, including Doppler spectral model, sea clutter composite amplitude statistical distribution model, etc..

This paper used two improved ways in heuristic optimization paradigm. Improving the mutation GA algorithm cloud offset the inherent shortcoming of the algorithm. The PSO-GA and PSO-CGA take the advantages of the two original algorithms, optimize the solution path, improve the individual utilization rate and reduce the error of the obtained results without reducing the solution time. This paper also proposes a new evaluation method of the heuristic search algorithm to measure the efficiency of the algorithm.

In future work, we will constantly improve the optimal solution algorithm and apply our method on deep networks such as CNN, GNN, and RNN.

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