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ESTIMATION OF THE ATMOSPHERIC DUCT FROM RADAR SEA CLUTTER USING ARTIFICIAL BEE COLONY OPTIMIZATION ALGORITHM

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Abstract—In this study, the Artificial Bee Colony Optimization (ABCO) algorithm has been proposed to estimate the atmospheric duct in maritime environment. The radar sea clutter power is calculated by the parabolic equation method. In order to validate the accuracy and robustness of ABCO algorithm, the experimental and simulation study are respectively carried out in the current research. In the simulation study, the statistical analysis of the estimation results in term of the mean squared error (MSE), mean absolute deviation (MAD) and mean relative error (MRE) are presented to analyze the optimization performance with different noise standard deviation, and the comparative study of the performance of ABCO and particle swarm optimization (PSO) algorithm are also shown. The investigation presented indicate that the ABCO algorithm can be accurately and effectively utilized to estimate the evaporation duct and surface-based duct using refractivity from clutter (RFC) technique in maritime environment. In addition, the performance of ABCO algorithm is clearly superior to that of the PSO algorithm according to the statistical analysis results, especially for the four-parameter surface-based duct estimation.

1. INTRODUCTION

Atmospheric duct is a type of abnormal atmosphere structure above maritime boundary layer, caused by the abrupt changes in the vertical atmospheric temperature and humidity profiles above the sea surface [1]. Under the atmosphere duct environment, the non-standard electromagnetic propagation can be observed, and the

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fundamental parameters and the performance of radar system and communication system can be drastically affected, such as the maximum operation range, creation of radar holes where the radar is practically blind, and strengthened sea surface clutter [2]. The atmospheric duct environment is usually described by the atmospheric modified refractivity profile. Two common abnormal refractivity structure in maritime environment are evaporation duct and surface-based duct, respectively. Especially, the evaporation duct is a nearly everlasting phenomenon. Although the probability of occurrence of the surface-based duct is less common than that of evaporation duct, the influence of surface-based duct on radar system and communication system is greater than that of evaporation duct. Consequently, estimation of atmospheric duct has been an important research subject owing to its considerable application in the design of radar system and communication system. The traditional ways of determining the modified refractivity profile include devices such as radiosondes, rocketsondes, microwave refractometers and lidar [2]. However, these methods have the disadvantages of high cost and difficult in practice. In recent years, refractivity from clutter (RFC) technique has been a novel and promising method to estimate the atmospheric duct instead of using the traditional ways mentioned above. Atmospheric duct is usually associated with increased sea clutter due to the heavy interaction between the sea surface and the electromagnetic wave trapped within the electromagnetic duct, and this unwanted sea clutter is a rich source of information about the low-altitude maritime environment and can be used to estimate the atmospheric duct [3]. Estimation of atmosphere duct using RFC technique is an inverse problem, and the relationship between the forward propagation model and atmosphere duct parameters is a complex nonlinear model. Recently, many researchers dedicated to the study of estimating the atmosphere duct [4–14] with efficient optimization methods, estimation model and analyze the performance of the optimization algorithm, and the detailed estimation steps and the latest research progress about the RFC technique can be founded in [4, 5]. Due to the nonlinear relationship between the forward propagation model and atmospheric duct parameters, the intelligent optimization algorithms, such as genetic algorithm (GA) [15], particle swarm optimization (PSO) [16], differential evolution (DE) [17] and ant colony optimization (ACO) [18], are good candidates to estimate the atmospheric duct from radar sea clutter.

The ABCO algorithm [19–21] is one of the most recently introduced swarm intelligence algorithm under the inspiration of intelligent behavior of honey bee swarm, which was firstly introduced by Karaboga and Basturk In ABCO algorithm, the optimization procedures are implemented by simulating the intelligent foraging behavior of a honeybee swarm to share information of bees for the purpose of finding the optimal solution. Furthermore, the optimization performance of ABCO algorithm has been proven to perform better than GA, DE and PSO for the multimodal benchmark function. Thus, the ABCO algorithm has been applied to the field of the design of linear array antenna and neuroimaging [22, 23].

In this study, the powerful and efficient ABCO algorithm is presented to estimate the evaporation duct and surface-based duct with the RFC technique. The accuracy and robustness of the ABCO algorithm is validated by the experimental data and synthetic data produced by the parabolic equation method. In addition, the optimization performance of ABCO algorithm is compared with that of PSO algorithm.

The remainder of this paper is organized as follows. In Section 2 gives the formula of radar sea clutter power and the objective function of the estimation problem. Section 3 briefly introduces the main procedures and flowchart of ABCO algorithm. The estimation results and performance analysis in Section 4 indicate the accuracy and robustness of ABCO algorithm, and the conclusions are drawn in Section 5.

2. THE FORWARD PROPAGATION MODEL AND OBJECTIVE FUNCTION

2.1. Parabolic Equation Method

In the atmospheric duct environment, the electromagnetic wave will be trapped into an electromagnetic duct layer, and it can give rise to the over the horizon propagation phenomenon and form the radar detection shadow zone. To estimate the atmospheric duct from radar sea clutter, we should quantitatively compute the propagation loss of the electromagnetic signal within the electromagnetic duct. The parabolic equation method is a useful tool to model the electromagnetic wave field distribution under the atmospheric duct environment due to its accuracy and stability. Given the initial field distribution, the split-step fourier transform solution of parabolic equation is given by [24]

$$\begin{aligned} &u(x_0 + \Delta x, z) \\ &= \exp\left[\left({}^{ik_0}\!/_2\right)\left[n^2-1\right]\Delta x\right] F^{-1}\left\{\exp\left[\left({}^{i\Delta x}\!/_{2k_0}\right)p^2\right] F[u(x_0, z)]\right\} \end{aligned} \tag{1}$$

where F and F^{-1} are the forward fourier transform and inverse fourier transform, respectively, and $p = k_0 \sin\theta$ denotes the transform variable. θ is the angle measured with respect to the horizontal direction, Δx the range step, k_0 the wavenumber, n the refractive index, and $u(x_0, z)$ the initial field distribution.

2.2. The Modified Refractivity Profile Model

To describe the negligibly small change of refractive index n with altitude in atmospheric duct environment, the refractivity N and modified refractivity M are generally used to define the change of n [25]

$$N = (n-1) \times 10^6 \tag{2}$$

$$M = N + \left(\frac{z}{R}\right) \times 10^6 \tag{3}$$

where z is the altitude and R the Earth's radius.

With the help of modified refractivity, the profile of evaporation duct [2] can be described by the log-linear evaporation duct using only one parameter

$$M(z) = M_0 + 0.125z - 0.125d \ln \frac{z + z_0}{z_0} \tag{4}$$

where z is the height above the mean height of sea surface, d the evaporation duct height, z_0 roughness factor whose typical value is 0.00015, and the constant M_0 usually taken as 330.0 M units.

While the surface-based duct can be usually represented by trilinear profile model using a four-parameter model

$$M(z) = M_0 + \begin{cases} c_1 z & \text{if } z < h_1 \\ c_1 h_1 + c_2(z - h_1) & \text{if } h_1 \leq z \leq h_2 \\ c_1 h_1 + c_2 h_2 + 0.118(z - h_1 - h_2) & \text{if } z > h_2 \end{cases} \tag{5}$$

where c_1 and h_1 are the slope and thickness of the base layer, whereas c_2 and h_2 are the slope and thickness of the inversion layer. The slope of the top layer is treated as a constant at 0.118 M-units/m. The modified refractivity profiles for evaporation duct and surface-based duct are given in Fig. 1.

2.3. Calculation of the Radar Sea Clutter Power

In the RFC technique, the received radar sea clutter power at different propagation distances are chosen as the input data. Taking the influence of atmosphere condition into account, the received radar sea clutter power can be obtained from radar equation [4]

$$P_c = \frac{P_t G_t^2 \lambda^2 F^4 \sigma}{(4\pi)^3 r^4} \tag{6}$$

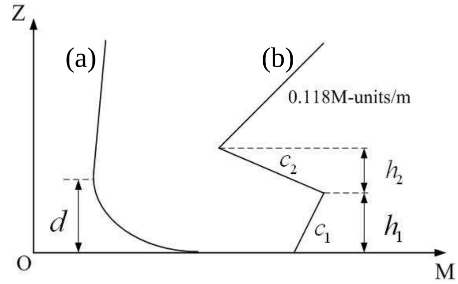

Figure 1. The modified refractivity profiles of (a) evaporation duct and (b) surface-based duct.

where P_t is the transmitted power, G_t the gain of transmitting antenna, λ the wavelength, r the distance between radar and illumination area, F the propagation factor, and σ the sea surface radar cross section, which can be expressed in term of normalized sea surface radar cross section σ_0. Finally, the received radar sea clutter power can be expressed in dB by

$$P_{c,\mathrm{dB}}(r, \mathbf{m}) = -2L + \sigma^{\circ} + 10\lg(r) + C \tag{7}$$

where L is the propagation loss obtained from the parabolic equation method mentioned above, C the constant terms in Eq. (6), and $\mathbf{m}$ the unknown environmental parameter vector. In general, the normalized sea surface radar cross section σ_0 is of difficulty to calculate with analytical or numerical methods at low grazing angle [26, 27], thus it can be acquired by the sea clutter theoretical model of GIT [28].

2.4. The Objective Function

The objective function of the optimizaiton problem adopted in this work is the least squares objective function, it can be expressed by [4]

$$f(\mathbf{m}) = \mathbf{e}^T\mathbf{e} \tag{8}$$

where

$$\mathbf{e} = \mathbf{P}_c^{obs} - \mathbf{P}_c(\mathbf{m}) - \hat{T} \tag{9}$$

$$\hat{T} = \bar{\mathbf{P}}_c^{obs} - \bar{\mathbf{P}}_c(\mathbf{m}) \tag{10}$$

where $\mathbf{P}_c^{obs}$ and $\mathbf{P}_c(\mathbf{m})$ are the observed and received radar sea clutter power vector at different propagation distance, whereas $\bar{\mathbf{P}}_c^{obs}$ and $\bar{\mathbf{P}}_c(\mathbf{m})$ are the mean observed and received radar sea clutter power across the elements in the vector, respectively.

3. INTRODUCTION OF THE ARTIFICIAL BEE COLONY ALGORITHM

It is well known that the RFC technique is an inverse problem, an efficient optimization algorithm needs to be selected to minimize the objective function for obtaining the best refractivity profile. In this section, the ABCO algorithm [19–21] is briefly introduced. The ABCO algorithm is an efficient optimization algorithm based on the intelligent behavior of honey bee swarm, the colony of bees consists of three essential components: employed bees, onlookers and scouts. The employed bee is used to search for the food sources, the onlooker bee makes a decision to choose the food sources by sharing the information of employed bee, and scout is used to determine a new food source if a food source is abandoned by the employed bee and onlooker bee. In the ABCO algorithm, the position of a food source corresponds to a possible solution of the optimization problem in the search space and the solution is evaluated by fitness function. In addition, only an employed bee exists for each food source, that is to say, the number of the employed bees is equal to the number of solutions. The flowchart of ABCO algorithm is shown in Fig. 2.

4. ESTIMATION RESULTS AND PERFORMANCE ANALYSIS

In the following, the estimation of evaporation duct and surface-based duct using RFC technique are investigated by the ABCO algorithm via the experimental and the simulation study. In addition, the statistical analysis of the estimation results and comparative analysis of the optimization performance of ABCO and PSO algorithm for the estimation of evaporation duct and surface-based duct with different noise standard deviation are also presented in the simulation study. For evaporation duct, only one parameter $\mathbf{m} = d$ needs to be estimated, whereas four-parameter $\mathbf{m} = (c_1, c_2, h_1, h_2)$ need to be estimated for surface-based duct. Therefore, the estimation of evaporation duct is relatively easier than that of surface-based duct. The lower and upper search bounds of the parameters used in the estimation are given in Table 1.

In this study, the radar sea clutter power from 10 Km to 50 Km are used to estimate the atmospheric duct, and the propagation loss in Eq. (7) are calculated at the effective scattering height given as 0.6 times the mean wave height [2]. The control parameters of each algorithm can be achieved by the trial and error method to obtain better performance in the estimation. For the evaporation duct

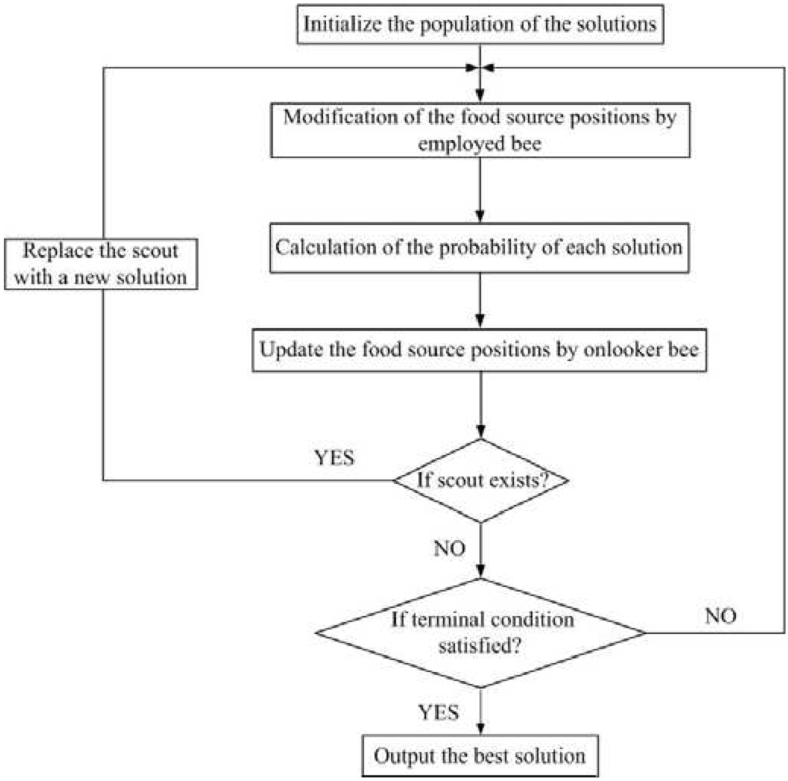

Figure 2. The flowchart of ABCO algorithm.

Table 1. The lower and upper search bounds of the parameters used in the estimation.

Parameter	Lower Bound	Upper Bound	Units
d	0.0	40.0	m
c_1	0.0	0.25	M-units/m
c_2	-3.5	-1.0	M-units/m
h_1	25.0	50.0	m
h_2	10.0	35.0	m

estimation, the control parameters of ABCO algorithm are given as follows: the number of colony size is 40, the number of food sources is 20, the maximum search limit is 100, and the maximum number of cycles is 100; the control parameters of PSO algorithm are given as follows: the population size is 10, the learning factor is 2.0, the inertia weight is 0.5, and the number of iteration is 20. Taking the randomness of parameter in the initialization stage and gaussian random noise into consideration, each run is repeated for 100 times to analyze the performance of ABCO and PSO algorithm for the evaporation duct and surface-based duct estimation with different noise standard deviation.

4.1. Estimation of Evaporation Duct

To validate the feasibility and effectiveness of the ABCO algorithm, the ABCO algorithm is firstly verified by the experimental data measured in East China Sea [29]. During the experiment, the radar system works at a frequency of 10 GHz, antenna height of 10 m, beam width of 0.7°, and the HH polarization is employed. The dependence of measured radar sea clutter power on the propagation distance is demonstrated in Fig. 3.

Figure 4 gives the comparison of the ABCO algorithm estimation modified refractivity profile with the measured profile, it can be seen that the modified refractivity profile estimated by ABCO algorithm is in excellent agreement with the measured one.

To further analyze the performance of ABCO algorithm, the simulation study are also carried out with synthesized radar sea clutter power produced by Eq. (7), and the gaussian noise with zero mean and different standard deviations are added to the synthesized radar sea clutter power to analyze the robustness of the optimization algorithm. The synthesized radar sea clutter power is generated at a frequency of 8 GHz, power of 91.4 dBm, antenna gain of 52.8 dB, antenna height

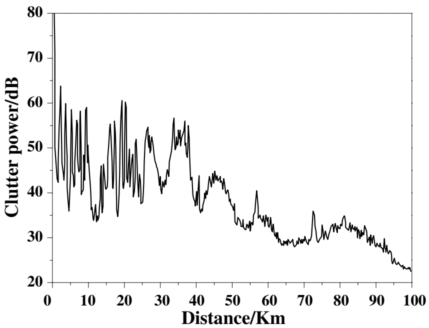

Figure 3. The dependence of measured radar sea clutter power on the propagation distance.

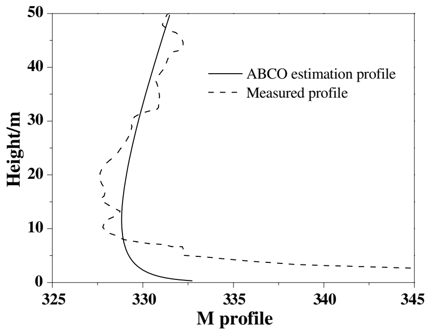

Figure 4. Comparison of the modified refractivity profile estimated by ABCO algorithm with the measured profile.

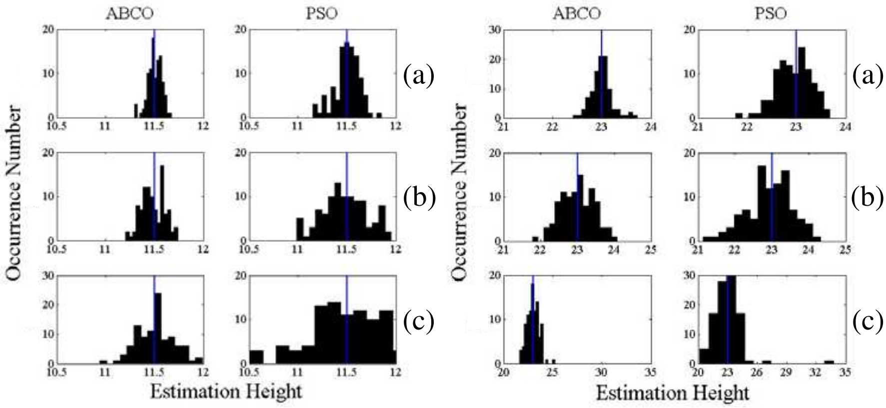

Figure 5. Comparision of the histograms of ABCO and PSO algorithm for the evaporation duct height estimation with different noise standard deviation. (a) 3 dB standard deviation. (b) 6 dB standard deviation. (c) 9 dB standard deviation.

of 7 m, beam width of 0.7°, 600 m range bins, and HH polarization is adopted. Here, we take the synthesized radar sea clutter power of evaporation duct height 11.5 m and 23.0 m with 3 dB, 6 dB, 9 dB noise standard deviation as the observed radar sea clutter power to analyze the performance of ABCO algorithm. In addition, the ABCO algorithm simulations are compared with those of the commonly used PSO algorithm for different noise standard deviation.

The histograms of estimation height for ABCO and PSO algorithm are given in Fig. 5, and the blue vertical lines stand for the actual evaporation duct height of synthesized radar sea clutter power. It is obvious that the statistical results of ABCO algorithm are more concentrated than those of PSO algorithm for different noise standard deviation, that is to say, the performance of ABCO is better than that of PSO. Overall, the estimation results of ABCO and PSO are accepted. However, the instability of PSO is obviously exhibited as the standard deviation reaches 9 dB as depicted in Fig. 5(c) for the 23 m evaporation duct height estimation. The part estimation height of PSO algorithm on the right side of the blue vertical line deviates greatly from the actual value. This phenomenon may be caused by the fact that the PSO algorithm has the shortcoming of sinking into local best.

To quantitatively analyze the performance of ABCO and PSO algorithm, the statistical analyses for the evaporation duct estimation in term of the Mean Squared Error (MSE), Mean Absolute Deviation

Table 2. The performance analysis of the evaporation duct height estimation results of ABCO and PSO ($d = 11.5\,\mathrm{m}$).

Noise level	ABCO			PSO		
	MSE	MAD	MRE	MSE	MAD	MRE
3 dB	0.005	0.055	0.47%	0.016	0.097	0.85%
6 dB	0.014	0.10	0.88%	0.052	0.186	1.62%
9 dB	0.036	0.15	1.30%	0.174	0.33	2.87%

Table 3. The performance analysis of the evaporation duct height estimation results of ABCO and PSO ($d = 23.0\,\mathrm{m}$).

Noise level	ABCO			PSO		
	MSE	MAD	MRE	MSE	MAD	MRE
3 dB	0.045	0.15	0.66%	0.13	0.30	1.27%
6 dB	0.23	0.36	1.58%	0.37	0.49	2.11%
9 dB	0.38	0.49	2.13%	2.37	0.96	4.19%

(MAD) and Mean Relative Error (MRE) [30] are illustrated in Tables 2 and 3. From Tables 2 and 3, we can see that the MSE, MAD and MRE of ABCO algorithm are slightly smaller than those of PSO algorithm with different noise level. That is to say, the accuracy and robustness of ABCO algorithm is slightly better than that of PSO algorithm for the evaporation duct estimation.

4.2. Estimation of Surface-based Duct

The histograms of simulation study of the ABCO and PSO algorithm for estimating the four-parameter surface-based duct are shown in Fig. 6, and the blue vertical lines stand for the actual surface-based parameters of synthesized radar sea clutter power. In our simulation, the radar system parameters are the same as those of the simulation for evaporation duct presented in Section 4.1. The actual surface-based duct parameters $\mathbf{m} = (0.13, -2.5, 40, 20)$ are chosen from the Ref. [1]. For the surface-based duct estimation, the control parameters of ABCO algorithm are given as follows: the number of colony size is 100, the number of food sources is 50, the maximum search limit is 100, and the maximum number of cycles is 500; the control parameters of PSO algorithm are given as follows: the population size is 50, the learning factor is 2.0, the inertia weight is 0.5, and the number of iteration is 50.

In Fig. 6, it is evident that there are different distribution

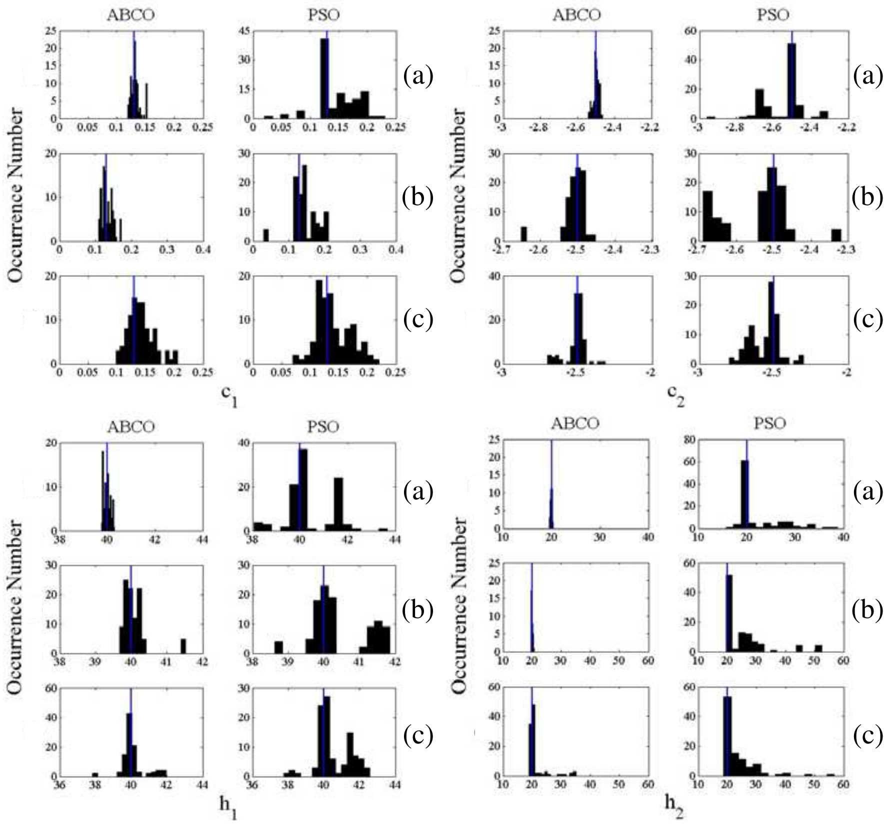

Figure 6. Comparision of the histograms of ABCO and PSO algorithm for the four-parameter surface-based duct estimation with different noise standard deviation. (a) 3 dB standard deviation. (b) 6 dB standard deviation. (c) 9 dB standard deviation.

features for the four-parameter in surface-based duct estimation, we can see that the distribution area of PSO algorithm is wider than those of ABCO algorithm for different noise standard deviation, it means that the accuracy and robustness of ABCO algorithm surpass the PSO algorithm. Especially in the histogram for the estimation of h_2 in Fig. 6, the accuracy and robustness of ABCO algorithm greatly outperform the PSO algorithm for the 3 dB and 6 dB standard deviation. This is due to the fact that the PSO algorithm have the drawback of premature convergence and trapping into local best when it comes to complex nonlinear objective function. However, the search capability of ABCO algorithm operator is strengthened by simultaneously taking the local and global search strategy into consideration, and the local best can be avoided by constantly adjusting the search space and producing new solution. Moreover, the instability of PSO algorithm is evident for the estimation of the h_2, and the instability of ABCO algorithm are also encountered in the estimation of h_2 with 9 dB standard deviation. This phenomenon indicates that although the performance of ABCO algorithm has been dramatically improved via the local and global search strategy at each iteration, the swarm intelligence algorithm has the disadvantage of sinking in to local best, which needs to be further investigated.

Similarly, the comparisons of performance analysis of the ABCO and PSO algorithm in terms of MSE, MAD and MRE mentioned above are also summarized in Tables 4–7. In Tables 5–6, it can be observed that the MSE, MAD and MRE of ABCO algorithm are slightly smaller than those of PSO algorithm with different noise standard deviation. That is to say, the performance of ABCO algorithm is slightly better than that of PSO algorithm for the estimation of c_2 and h_1 in surface-based duct. In contrast, the MRE of PSO algorithm in Table 4 and the MSE, MRE of PSO algorithm in Table 7 are considerably greater than those of ABCO algorithm, these indicate that the stability of ABCO algorithm is much better than that of PSO algorithm for the estimation

Table 4. The performance analysis of the surface-based duct estimation results of ABCO and PSO (c_1).

Noise level	ABCO			PSO		
	MSE	MAD	MRE	MSE	MAD	MRE
3 dB	7.5E-5	0.006	4.78%	0.0015	0.027	20.7%
6 dB	2.3E-4	0.012	9.2%	0.0015	0.027	20.7%
9 dB	2.4E-4	0.018	14.1%	0.001	0.025	19.2%

Table 5. The performance analysis of the surface-based duct estimation results of ABCO and PSO (c_2).

Noise level	ABCO			PSO		
	MSE	MAD	MRE	MSE	MAD	MRE
3 dB	2.3E-4	0.011	0.46%	0.013	0.073	2.93%
6 dB	0.0015	0.02	0.88%	0.01	0.07	2.7%
9 dB	0.0043	0.04	1.57%	0.013	0.08	3.4%

Table 6. The performance analysis of the surface-based duct estimation results of ABCO and PSO (h_1).

Noise level	ABCO			PSO		
	MSE	MAD	MRE	MSE	MAD	MRE
3 dB	0.018	0.11	0.27%	1.14	0.72	1.8%
6 dB	0.15	0.23	0.57%	0.84	0.63	1.59%
9 dB	0.42	0.4	0.98%	1.22	0.79	1.97%

Table 7. The performance analysis of the surface-based duct estimation results of ABCO and PSO (h_2).

Noise level	ABCO			PSO		
	MSE	MAD	MRE	MSE	MAD	MRE
3 dB	0.03	0.14	0.71%	25.8	2.75	13.7%
6 dB	0.08	0.22	1.1%	90.7	5.4	26.97%
9 dB	14.7	1.55	7.75%	51.0	3.8	19.2%

of c_1 and h_2 in surface-based duct. As a whole, the performance of ABCO algorithm distinctly is better than that of PSO algorithm for the surface-based duct estimation.

Since the modified refractivity profile of surface-based duct is depicted using a four-parameter refractivity profile model, so the difference of propagation loss between the estimation refractivity parameters and the actual refractivity parameters are calculated by the parabolic equation method, where the estimation refractivity parameters are obtained by averaging over the 100 times estimation results. Here, the difference of propagation loss is defined by subtracting the propagation loss simulated by actual refractivity parameters from the propagation loss simulated by estimation refractivity parameters.

Figure 7 demonstrates the comparison of the difference of propagation loss simulated by the surface-based duct parameters estimated by the ABCO and PSO algorithm with different noise standard deviations. It can be clearly seen that the differences of propagation loss estimated by ABCO algorithm are less than those of PSO algorithm for the same standard deviation, which also validates the conclusion drawn above for the surface-based duct estimation in Fig. 6 and the performance analysis in Tables 4–7.

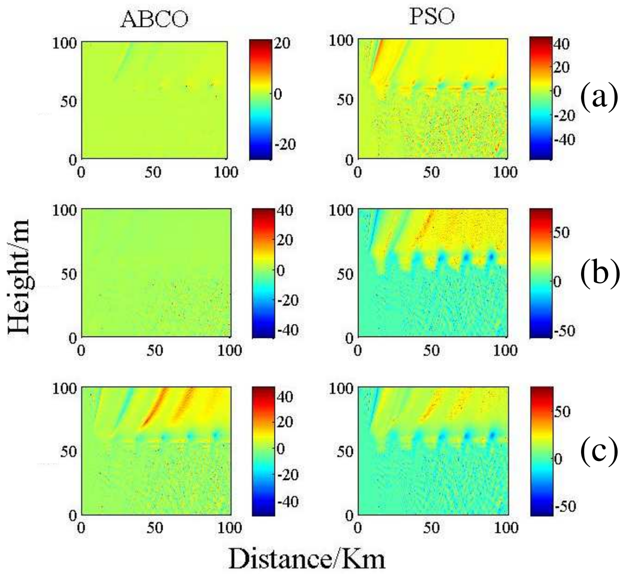

Figure 7. Comparision of the difference (dB) of propagation loss between the ABCO and PSO estimation results with different noise standard deviation. (a) 3 dB standard deviation. (b) 6 dB standard deviation. (c) 9 dB standard deviation.

5. CONCLUSION

In this paper, the powerful and efficient ABCO algorithm has been proposed to estimate the evaporation duct and surface-based duct in maritime environment. The experiment and simulation are used to validate the accuracy and robustness of ABCO algorithm. For the experimental study, the radar sea clutter power data gathered in East China Sea are used to estimate the evaporation duct, and the estimated profile is in excellent agreement with the measured one. For the simulation study, the statistical analyses in term of MSE, MAD, MRE are adopted to analyze the optimization performance, and the comparative study of the ABCO and PSO algorithm is also involved. The investigation presented indicates that the ABCO algorithm can be accurately and effectively utilized to estimate the evaporation duct and surface-based duct using RFC technique in maritime environment. In addition, the performance of ABCO algorithm is superior to that of the PSO algorithm, especially for the four-parameter surface-based duct estimation. It should be noted that the improved or hybrid optimization scheme will be evaluated in the future investigation.

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