Application of the Particle Swarm Optimization for Determination of Parameters of the Atmosphere over the Sea for the Radar Station

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Abstract

In a radar-location there is an effect of emergence of a layer of evaporation over a surface of the water which begins to influence distribution of radio waves there is a distribution trajectory curvature to the subsequent dispersion of power about a sea surface. The technique of measurement of height of a layer consists in use of this power. Since the relationship between the layer parameters and the power is nonlinear, in the conditions of modern theory it is impossible to get an analytical solution of the problem. For search of parameters of a layer the method of "a swarm of particles" and his modification by "Levi's flight" have been used. As function of optimization the modified refraction index is chosen, with his help channels of evaporation of varying complexity are described. Experiments by determination of parameters of a layer by two methods, and also their comparison are made.

1 Introduction

The Global methods of optimization are widely used in various problem of radar-location. The features of such problems are often non-linearity, nondifferentiability, lack of analytical expression, multi-extremality, high computational complexity of optimized functions and etc.

The global problem in radar-location is the effect of the emergence of an evaporations layer above the water surface. This atmospheric layer begins to affect the propagation of radio waves - there is a curvature of the trajectory of propagation. The curvature of the trajectory of the ray is associated with the phenomenon of refraction. The appearance of so-called waveguide channels entails a change in the operating parameters of the radar station-a reduction of the maximum range, an increase in the number of sea jammers, and the appearance of radar holes.

Conditionally, the parameters of the atmosphere can be measured with rocket probes and weather station predictions. However, these methods are expensive and can not provide real-time channel parameters.

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Evaporation channel usually arises in the case of an abnormal atmospheres state. Such parameters are temperature, atmospheric pressure, wind speed, and etc. Part of the power is lost, since there is scattering associated with the state of the sea surface. The technique for measuring the height of a layer is to use this power. Part of the power is lost, since there is scattering associated with the state of the sea surface. The technique for measuring the height of a layer is to use this power.

2 Simulation of the Radar Sea Clutter

Articles [Karimian, 2012], [Wang & Wu, 2009], [Zhang et al., 2015] examines the physics of the process and introduces the appropriate evaporation duct.

A forward simulation of received radar sea clutter power has to be performed, and its accuracy determines the veracity of evaluating the performances of radar systems and effects the precision of retrieved duct parameters. Using the classical radar equation, received radar clutter power can be calculated as follows (in dB):

$$P_{rc}(r, m) = -2L(r, m) + 10log_{10}(r) + \sigma^0(r) + C \tag{1}$$

where L is one-way propagation loss in ducts and obtained using the split-step fast Fourier transform (FFT) parabolic equation (PE).r is distance. $\sigma^0(r)$ is the normalized sea surface radar cross section (scattering coefficient) at r. C is a constant that includes wavelength, transmitter power, antenna gain, etc. Obviously, $\sigma^0(r)$ and L must be calculated accurately, if we want to get an accurate radar sea clutter power P_{rc}.

2.1 Evaporation Duct Model

Normally, the atmospheric refractivity has a negative slope of the altitude. In this condition, electromagnetic waves would slowly move away from the surface. If the negative slope is stronger than the curvature of the earth, the wave will be partially trapped and forced to bend downward, and an atmospheric duct is formed. In troposphere, refractivity (N) is usually expressed as:

$$n = \tfrac{77.6}{T}(p + \tfrac{4810e}{T}) \tag{2}$$

where T, p, and e represent absolute temperature (K), atmosphere pressure (hpa) and water vapor pressure (hpa) of atmosphere, respectively.

The modified refractivity (M) is usually introduced in the form of at earth. N and M can be computed as

$$\tfrac{dM}{dh} \leq 0(M - units/km) \tag{3}$$

From, (2) and (3), ducts occur when M satisfies:

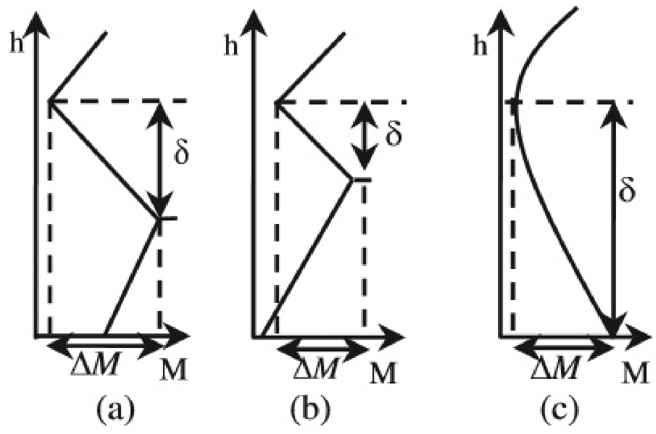

Figure 1: Most common three duct types. (a) Surface-based duct. (b) Elevated duct. (c) Evaporation duct.

Duct models play an important role in retrieving duct parameters, and they effect the nal retrieved results. For sea environments, there are three major sea ducts frequently encountered (Fig. 1): Surface based ducts, elevated ducts, and evaporation ducts. Because evaporation ducts are the main consideration, a single parameter exponent model for Fig. 2(c) is given by Equation (4)

$$M(z) = M_0 + 0.125z - 0.125dln[\frac{z+z_0}{z_0}] \tag{4}$$

where z is height; d is the evaporation duct height; M is the evaporation duct strength; $z0 = 1.5 * 10^{-4}$. $M0$ is the modified refractivity at sea surface; its typical value is $370M$. This model has been extensively applied and especially precise to evaporation duct.

3 The Particle Swarm Optimization

The global methods optimization used are considered in [Karpenko, 2014]. The particle swarm optimization (PSO) is based on the socio-psychological behavioral model of the crowd. The development of the algorithm was inspired by such tasks as modeling the behavior of birds in the flock and fishes in a jamb. The goal was to discover the basic principles, thanks to which, for example, the birds in the pack behave surprisingly synchronously, changing direction of the movement.

3.1 Particle Swarm Optimization

By modern time, the swarm algorithm [Wang & Wu, 2009] has evolved into a highly efficient optimization algorithm, often competing with other optimization algorithms.

Iterations in the algorithm are

$$X_i' = X_i + V_i \tag{5}$$

$$V_i = b_l V_i + U_{|X|}(0; b_c) \oplus (X_i^* - X_i) + U_{|X|}(0; b_s) \oplus (X_i^{**} - X_i) \tag{6}$$

where X_i V_i are position and velocity of the each particle. is vector space of the local best values; is vector space of the global best values; $\oplus$ is direct sum vector space.

3.2 Particle Swarm Optimization via Levy Flight

There is also a modification of the particle swarm optimization via Levy Flight (LPSO) [Zhang et al., 2015].

The Levi flight is a special class of random motion, consisting of a series of short displacements, with long displacements occurring between them. Many studies have shown that the flight behavior of birds, insects, herbivores has the typical features of Levy's flight. This movement can be used as a global search algorithm.

The Levi flight can be successfully applied in a swarm of particles, and the rate of convergence and accuracy of the method will be higher.

A Levy flight is applied in PSO to generate a new solution from a particle's position xo using Eq. (8)

$$X_i^{t+1} = X_i^t + \alpha \oplus Levy(\lambda) \tag{7}$$

where α is the step size. The product $\oplus$ means entrywise multiplications. $Levy(\lambda)$ is a Levy flight, which provides a random walk while their random steps are drawn from a Levy distribution, $Levy(\lambda)$: $1 < \lambda < 3$, which has an infinite variance with an infinite mean. The Levy distribution, named after the French mathematician Paul Pierre Levy, is a continuous probability distribution for a non-negative random variable, which belongs to the α stable distribution.

Levy Flight can be described as

$$Levy(\lambda) = 0.01\frac{\mu}{\upsilon}(x_i^t - X_i^{**}) \tag{8}$$

where μ and υ all follow a normal distribution, $\mu \sim N(0, \sigma_\mu^2)$, $\upsilon \sim N(0, \sigma_\upsilon^2)$. the value of and can be calculated by the follow equation:

$$\begin{aligned} \sigma_\mu &= (\frac{\Gamma(\lambda)\sin(\pi(\lambda-1)/2)}{2^{(\lambda-2)/2}\Gamma(\lambda/2)(\lambda-1)})^{1/\lambda-1} \\ \sigma_\upsilon &= 1 \end{aligned} \tag{9}$$

3.3 The Steps of PSO and LPSO

PSO algorithm has a good convergence speed in the early calculation period, but it is easily trapped into a local optimal solution in later calculations. PSO can maintain a high population diversity in the early period. However, with the increase in iterations, the majority of the groups concentrate in the vicinity of an optimal solution. In order to deal with this problem, the Levy flight was introduced into standard PSO. That is, when each particle updates the position, the objective function is not directly calculated, but it further updates individual positions via Levy flight, and then calculates the value of the objective function. LPSO has a better local search ability, which can improve the algorithm's convergence rate and efficiency.

The detailed steps for parameter estimation with the LPSO algorithm can be described as follows: Step 1: Initialize parameters and all the particles.

Step 2: Begin the iteration process.

Step 3: Evaluate the fintes function of each particle and determine the global and local best value.

Step 4: According to the fitness, update position and velocity.

Step 5: If the LPSO algorithm is used, then updating the position using the Levy flight.

Step 6: Go to step 3 and check whether the stopping criterion is met.

Flowchart of the algorithms is shown in Fig 2. Flowchart of the algorithms is shown in Fig 2.

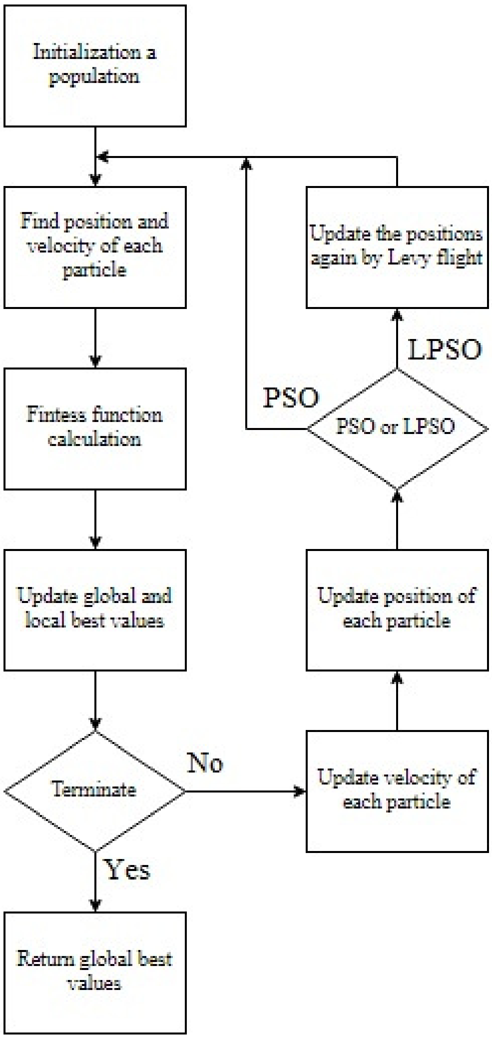

Figure 2: Flowchart of the algorithms.

4 Experiments

To test the effective of optimization algorithms we employ functions of Rastrigin and Schwefel. After we use PSO and LPSO for find evaporation duct layer.

4.1 Optimization of the Rastrigin Function

Rastrigin function (Fig. 3) is a typical example of non-linear multimodal function. Finding the minimum of this function is a fairly difficult problem due to existing of large number of local mimina.

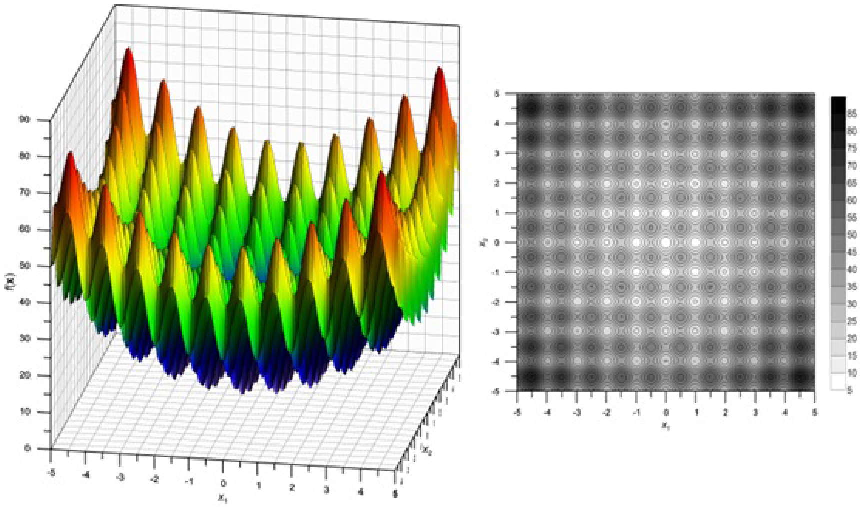

Figure 3: Rastrigin function of two variable: (a) In 3D (b) Contour

On an n-dimensional domain it is defined by

$$f(X) = 10n + \sum_{i=1}^{n} [x_i^2 - 10cos(2\pi x_i)], \tag{10}$$

where it has a global minima at $x = 0$ where $f(x) = 0$.

The result of optimization are shown in Table 1.

Table 1: Results

h, m	PSO		LPSO	
X	x1	x2	x1	x2
	-0.99	-0.99	0.05	0.03
f(X)	1.98		0.67	

PSO was at the local minina, while LPSO was at the global minima.

4.2 Optimization of the Schwefel's Function

The Schwefel function (Fig. 4) is complex, with many local minima.

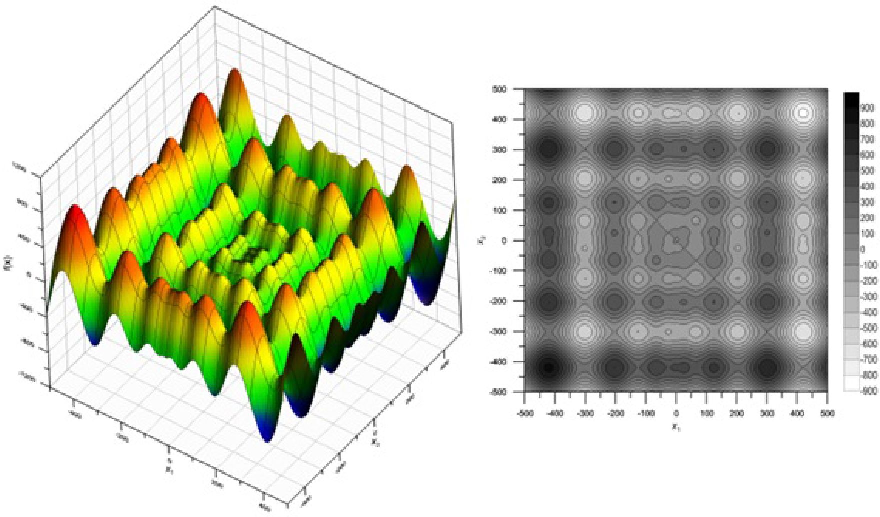

Figure 4: Schwefel's function of two variable: (a) In 3D (b) Contour

On an n-dimensional domain it is defined by

$$f(X) = \sum_{i=1}^{n}[\sqrt{|2\pi x_i|}], \tag{11}$$

where it has a global minima at $X = 420.9687$ where $f(x) = -418.9829n$.

The result of optimization are shown in Table 2.

Table 2: Results

h, m	PSO		LPSO	
X	x1	x2	x1	x2
	205.58	401.57	421.04	421.49
f(X)	-574.2		-873.93	

PSO failed in the optimization task, but LPSO successfully get the global minima.

4.3 Optimization of the Evaporation Duct Model

Purpose-oriented function has several local minimal (Fig. 5), but the global minima is up to 100 meters.

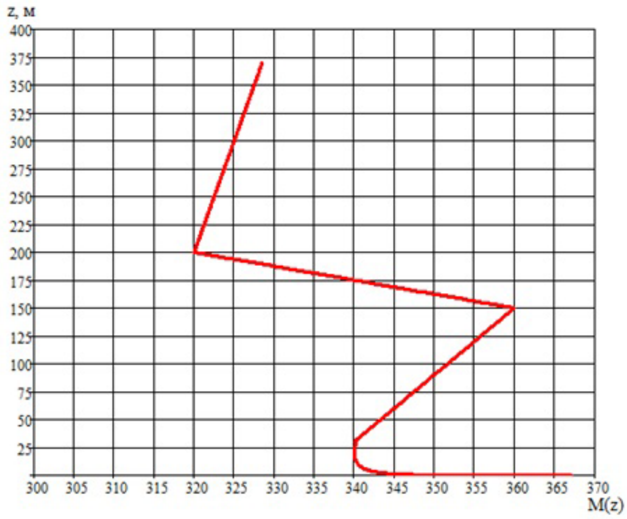

Figure 5: Modified refractivity, d = 20

The results of the experiment are shown in Table 3.

Table 3: Results

h, m	PSO		LPSO	
opt	z,m	%	z, m	%
20	21.25	6.25	20.065	0.325

If we change altitude Evaporation layer, result of optimization are shown in Table 4 and Fig. 6.

Table 4: Results

h, m	PSO		LPSO	
opt	z,m	%	z, m	%
20	20.085	0.425	20.065	0.325
30	30.059	0.197	30.053	0.177
40	40.081	0.17	40.112	0.28

Another important parameter that should be evaluated is the complexity of each method. The amount of time spent per iteration in each optimization algorithm is different.

In both algorithms at each iteration, it is necessary to calculate the value of purpose-oriented function, update the global and local minima, and update the position. In the modification by Levy's flight, the Levi step is additionally calculated.

As a result, the total laboriousness of the PSO is

$$R_{PSO} = \tau_0(2N + i) + \tau_1 N + \tau_2 N, \tag{12}$$

where τ_0, τ_1, τ_2 are time of the each operations.

Labor intensity LPSO is

$$\begin{aligned} R_{LPSO} &= R_{PSO} + R_{Levy} \\ R_{Levy} &= \tau_3 + 2\tau_4 + \tau_2 N \end{aligned} \tag{13}$$

In the experiment it was discovered that the LPSO find more precise solution. Graph of the accuracy of the solution from convergence is shown in Fig 6.

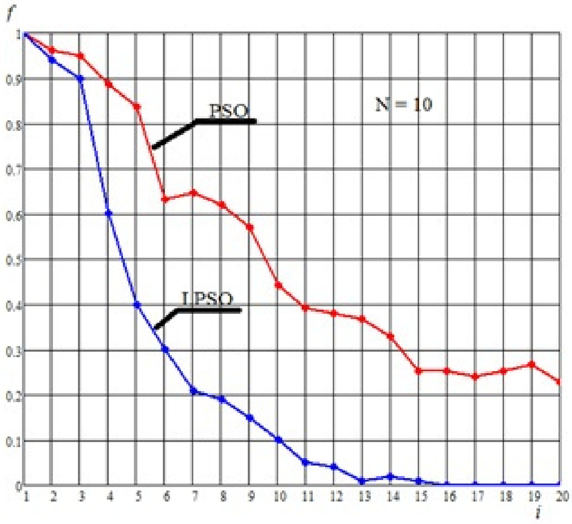

Figure 6: The result of the effectiveness of methods PSO and LPSO.

For choose an optimization algorithm, it is necessary to take into account not only the accuracy of the solution and the rate of convergence, but also the laboriousness of the methods. Modification of the particle swarm method leads to an increase in the rate of convergence, with a significant increase in accuracy possible. However, the use of Levy's method demand many complicated calculations.

5 Conclusion

Based on the results of the experiments it can be concluded that the proposed methods Particle Swarm Optimization (PSO) and Particle Swarm Optimization via Levy Flight (LPSO) successfully cope with the problem. The accuracy and speed of convergence of the second method is higher. This is primarily due to the fact that the particles moving by the flight of Levi are able to continue moving even with good accuracy, thereby improving the result. The convergence rate of the second method is also higher. This is due to the fact that apart from the usual exchange of information with each other, the particles carry out additional movement by the flight of Levi, thereby achieving goals faster. If we talk about laboriousness, then Levy's flight is a more labor-intensive method, so it is worth choosing between the rate of convergence on one iteration and the computational cost.

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