The Complex Blind Deflation Algorithm Based Particle Swarm Optimization with Survival of the Fittest Mechanism

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***Abstract*—For multi-constraint nonlinear optimization, this paper puts forward a complex blind deflation algorithm based particle swarm optimization with survival of the fittest mechanism(CBD-PSOSFM) which has faster convergence speed, and then gives a quantificational formula of the improved convergence speed, discusses implement method and the rule of parameters design; Because of the blind source separation (BSS) optimization characteristic in nature, the algorithm can be used to implement semi-BSS with nonlinear multi-constraint. For active object echo detection, the paper sets up fitness function with the multi-constraint like as kurtosis, energy and outline and forms the complex blind deflation algorithm. Finally, the simulation experiment of blind deflation to complex echo validates the algorithm's validity and faster convergence capability.**

Keywords-particle swarm optimization (PSO); complex signal; blind deflation; algorithm

I. INTRODUCE

The particle swarm optimization (PSO) is a stochastic global optimization method [1] offered by J. Kenney and R.C. Eberhart in 1995, which simulates birds to search food; Clerc makes the PSO certain convergence by using convergence factor model. The above-cited forms the standard PSO algorithm. For different application, the PSO may not come to the best effect, so the improved PSO algorithm appeared largely [3-6].

II. MULTI-CONSTRAINT PARTICLE SWARM OPTIMIZATION ALGORITHM

Given proper constraint can heighten convergence speed by shrinking feasible domain. In the traditional optimization theory, additional constraint may cause the continuous differentiability to be destroyed, which invalidates numerous usual optimization algorithms, but the PSO is good at the optimization with nonlinear multi-constraint. For the BSS with constraint, namely the semi-BSS, not only deflates the only interesting object signal by using some experiential characteristics, but also heightens convergence speed.

A. The Particle Swarm Optimization with Survival of the Fittest Mechanism

In the beginning of CBD-PSOSFM, it is necessary to avoid the particles running into local extremum by using abundant particles. As the trend of convergence is formed, too many particles are unnecessary for searching extremum. So we can decrease particle number to increase the convergence speed in the course of optimization.

The constraint PSO can express as the following:

$$\begin{cases} \mathbf{x} = arc\min f(\mathbf{x}) \\ s.t. \quad \mathbf{h}(\mathbf{x}) = \mathbf{0} \end{cases}$$

$$\mathbf{h}(\mathbf{x}) = \begin{bmatrix} h_1(\mathbf{x}) & h_2(\mathbf{x}) & \cdots & h_N(\mathbf{x}) \end{bmatrix}^T$$

The $\mathbf{x}$ is a M dimension particle vector, the $\mathbf{h}(\cdot)$ is a N dimension multi-constraint function vector.

The optimization based penalty function is:

$$\mathbf{x} = arc\min F(\mathbf{x},\mathbf{m})$$

$$F(\mathbf{x},\mathbf{m}) = f(\mathbf{x}) + \mathbf{m}\cdot\mathbf{h}^2(\mathbf{x})$$

The penalty coefficient vector is:

$$\mathbf{m} = \begin{bmatrix} m_1 & m_2 & \cdots & m_N \end{bmatrix}$$

The particles moving way is:

$$\mathbf{v}_i = k\cdot\left[\mathbf{v}_i + c_1\cdot r_1\cdot(\mathbf{p}_i - \mathbf{x}_i) + c_2\cdot r_2\cdot(\mathbf{g} - \mathbf{x}_i)\right]$$

$$k = \frac{2}{\left|2 - \phi - \sqrt{\phi^2 - 4\cdot\phi}\right|}$$

$$\mathbf{x}_i = \mathbf{x}_i + \mathbf{v}_i$$

$$\phi = c1 + c2 > 4\,,\, i = 1,2,\cdots N(k)$$

c_1, c_2 are two non-minus constants; r_1, r_2 are two random numbers in $[0,1]$; $v_i \in [-v_{\max} \quad v_{\max}]$, $v_{\max}$ is confirmed by search domain.

$N(k)$ is the particle swarm scale function which is the descending one:

$$N(k) = \begin{cases} M & k \le m_1\cdot K \\ \text{int}(M + \dfrac{(M-C)\cdot(k - m_1\cdot K)}{(m_1 - m_2)}) & m_1\cdot K < k < m_2\cdot K \\ C & k \ge m_2\cdot K \end{cases}$$

The survival of the fittest mechanism: Firstly, the CBD-PSOSFM starts in abundant particle number that ensures the solution's diversity. When iterative times is more than $m_1\cdot K$, the survival of the fittest mechanism brings into effect by reserving the $N(k)$ particles with bigger fitness value for heightening convergence speed. When iterative times is more than $m_2\cdot K$, the particle number is maintained on C until to the end. The CBD-PSOSFM consumes less

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iterative times than the traditional one about: $(M-C)(2-(m_1+m_2))K/2$.

The parameters design rule: For enactment total iterative times K, the parameters m_1, m_2 scale are : $0.0 \sim 1.0$, and $m_2 > m_1$; For more local extremum, m_1 trends to bigger value which controls iterative times with more particles. For slower convergence speed, m_2 trends to smaller value which controls iterative times to the acceptable solution with less particles. C is the necessary particle number for the precision solution.

B. The Particle Swarm Optimization Algorithm with Survival of the Fittest Mechanism Far-ranging Applicability

Since no more special hypotheses to the CBD-PSOSFM, the particle can be scalar, vector or multi-dimension matrix; the particle can be integer, real number or complex number. So the CBD-PSOSFM can be extended to complex matrix in nature.

III. The Complex Blind Deflation Based Multi-Constraint Particle Swarm Optimization with Survival of the Fittest Mechanism

It is a desired goal for underwater detector to find object in numerous interferences. The BSS offers a way for active object detector to separate object signal from interferences [7]; especially as known fractional experiential information, the semi-blind deflation is a good choice to heighten detection efficiency. Although the traditional constraint optimization can solve some anti-interference BSS question, it requests the nonlinear object function with first and twice continuous differentiability [8-9], which restricts its appliance largely. This paper puts forward the complex blind deflation algorithm based particle swarm optimization with survival of the fittest mechanism (CBD-PSOSFM) algorithm to deflate echo by turn a blind eye to inferences, which avoids identifying the separated signal's sort, heightening convergence speed, improving stability and simplifing operation.

A. The Fitness Function with the Multi-constraint Like as Kurtosis, Energy and Outline

The complex fitness function with the multi-constraint like as kurtosis, energy and outline is expressed as the following:

$$f(\mathbf{w}) = (k_4(y(n))-a)^2 + (k_2(y(n))-b)^2 + (\rho(y(n),c(n))-c)^2$$

$$y(n) = \mathbf{w}^H \cdot \mathbf{x}(n)$$

$$k_4(y(n)) = E[y^4(n)] - 3\cdot E^2[y^2(n)] - 4\cdot E[y^3(n)]E[y(n)] + 12\cdot E[y^2(n)]E^2[y(n)] - 6\cdot E^4[y(n)]$$

$$k_2(y(n)) = E[y^2(n)] - E^2[y(n)]$$

$$\rho(y(n),c(n)) = \frac{\sum_{n=1}^{N} |y(n)|\cdot c(n)}{\sqrt{\sum_{n=1}^{N} y^2(n)}\cdot\sqrt{\sum_{n=1}^{N} c^2(n)}}$$

The $\mathbf{x}(n)$ $n = 1,2,3\cdots,N$ is a L dimension complex mixed observed signal vector; the $\mathbf{w}$ is a L dimension complex particle vector; the $k_2(y(n)), k_4(y(n))$ is the twice cumulant and quartic cumulant of the deflated signal; the $\rho(y(n),c(n))$ is a cross-correlation coefficient between the deflated signal $y(n)$ outline and the emissive signal outline; the a,b,c is the emissive signal quartic cumulant, twice cumulant and the perfect cross-correlation coefficient between the deflated signal outline and the emissive signal outline.

IV. The Simulation Experiment

In order to validate the CBD-PSOSFM's validity and convergence speed improvement, we generate the complex echo and three complex interferences. The CBD-PSOSFM will deflate the only object echo from the mixed observed signals.

A. The Simulation Condition

The sample frequency is $f_s = 10kHz$, the sample time is $T = 0.2s$, the single complex object echo signal and three complex interference signals is expressed as the following respectively:

The sine wave with trapezoid outline (object):

$$s_1(t) = A_1 \cdot Trip(t)\cdot \sin(2\pi f_1 t);$$

$$A_1 = 1.0V,\ f_1 = 500Hz.$$

$Trip(t)$ is the trapezoid outline:

$$Trip(t) = \begin{cases} 40\cdot(t-0.025) & 0.025 < t \le 0.05 \\ 1 & 0.05 < t \le 0.15 \\ 40\cdot(0.15-t)+1 & 0.15 < t \le 0.175 \\ 0 & other \end{cases}$$

The Gauss white noise (interference):

$$s_2(t) = A_2 \cdot randn(t);$$

$$A_2 = 1.0V.$$

The first super-Gauss signal (interference):

$$s_3(t) = A_3 \cdot \cos(2\cdot\pi\cdot f_2\cdot t)\cdot \sin(2\cdot\pi\cdot f_3\cdot t)^7;$$

$$A_3 = 1.0V,\ f_2 = 100Hz,\ f_3 = 150Hz.$$

The second super-Gauss signal (interference):

$$s_4(t) = A_4 \cdot ((\mathrm{mod}(10000\cdot t, 23)\text{-}11)/9)^5;$$

$$A_4 = 0.6V.$$

The mixture model is: $\mathbf{x}(t) = \mathbf{A}\cdot\mathbf{s}(t)$;

The $\mathbf{s}(t)$ is a object and interferences signal vector, the $\mathbf{x}(t)$ is a observed signal vector and the $\mathbf{A}$ is a complex random mixture matrix;

$$A=\begin{bmatrix} 0.1702+0.6066i & 0.5304+0.5803i & 0.5232+0.3658i & 0.2917+0.4676i \\ 0.0899+0.0126i & 0.3474+0.7536i & 0.4345+0.7683i & 0.6204+0.9560i \\ 0.8537+0.0382i & 0.1768+0.3282i & 0.1832+0.0654i & 0.4992+0.3257i \\ 0.4887+0.9220i & 0.7452+0.2401i & 0.9916+0.9285i & 0.9936+0.2955i \end{bmatrix}$$

The complex object echo signal and complex interference signals are showed in the Fig.1; their real parts is showed in the Fig.2; the complex mixed observed signals are showed in the Fig.3.

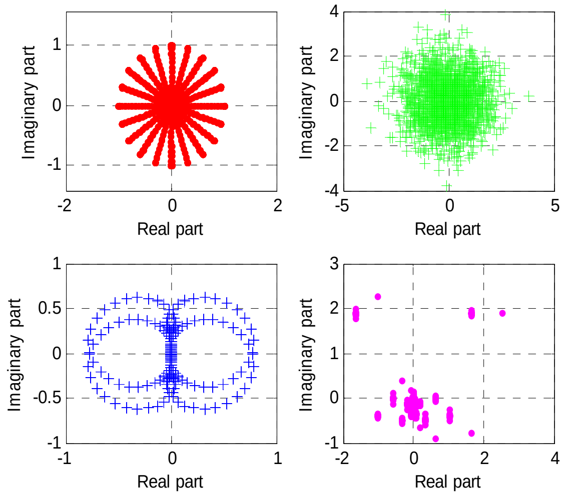

Figure 1. The complex object echo and interference signals

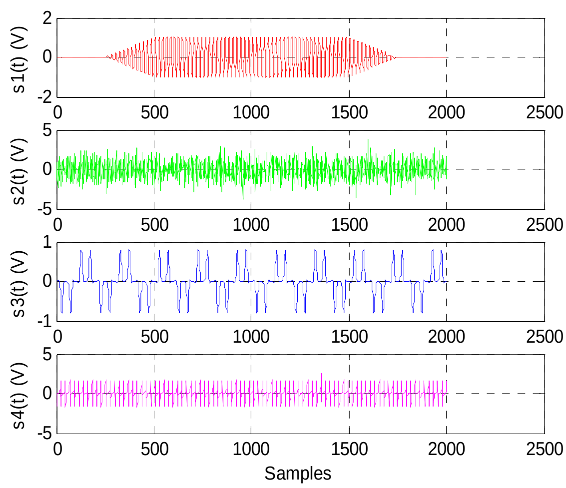

Figure 2. The complex object echo and interferences real part

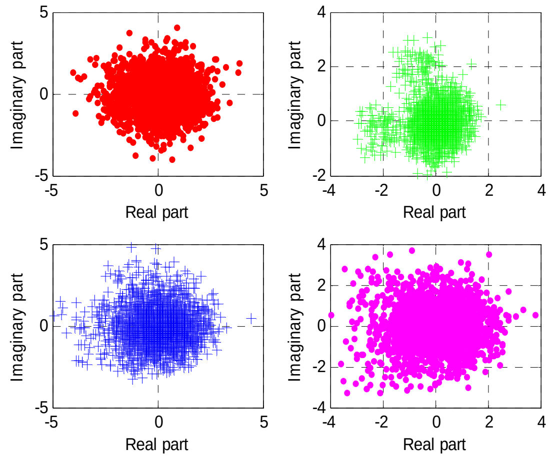

Figure 3. The four complex mixed observed signals

B. *The Simulation Result*

In simulation experiment, the fitness function parameter values are: $a=-0.1301, b=0.583, c=1$; the parameter values of survival of the fittest mechanism are: $K=220, M=100, C=60, m_1=0.5, m_2=0.68$.

Both the standard PSO and the CBD-PSOSFM can deflate the object echo signal from complex observed signals in same complex mixture matrix. The following Fig. 4 and Fig 5 show the separated complex object echo signal and its real part.

C. *The Performance Contrast and Conclusion*

In generally, the faster particle eliminative speed will affect solution precision, but the slower may not improve convergence speed obviously. The experiment result shows that the CBD-PSOSFM's convergence is quicker than the one based standard PSO about 16.34% in the homologous precision. The following Fig. 6 shows the performance index (PI) mean iterative convergence situation after 100 Monte Carlo tests.

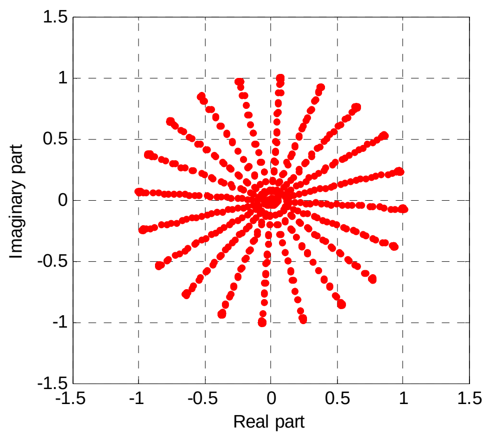

Figure 4. The separated complex object echo signal

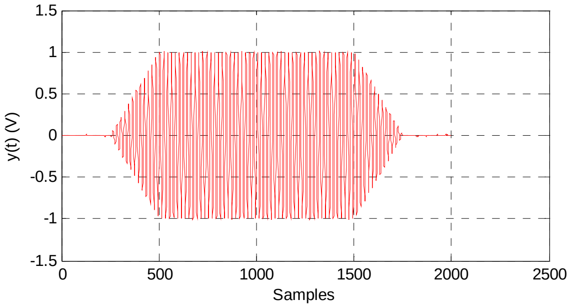

Figure 5. The separated object echo signal real part

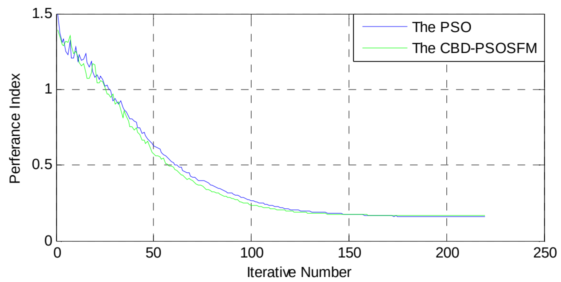

Figure 6. The PI iterative convergence situation

V. CONCLUSION

The CBD-PSOSFM is a rising colony stochastic optimization technology whose idea is comes from artificial intelligence and evolvement computational theory. Like the other optimization based colony search, the CBD-PSOSFM can solve many complex optimization questions, especially for nonlinear object function optimization question. What's more, the CBD-PSOSFM has the general adaptability, parallel operation, expansibility, less adjustable parameter, easy realization and faster convergence speed, which make the CBD-PSOSFM attain broad application.

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