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An Improved Particle Swarm Optimization Algorithm for Seismic Wavelet Estimation

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Abstract: An improved particle swarm optimization algorithm is presented in this study. The new method proposes a linear time-varying acceleration co-efficient and brings in two mutations including differential mutation and random mutation. Also, some betterment is made over the bound constraints which keep the escaped particles diversity. At last, this new method is applied to seismic wavelet estimation. Numerical data tests demonstrate that the method is capable of extracting wavelets with relatively higher accuracy.

Key words: Acceleration co-efficient, high-order cumulant, particle swarm optimization, wavelet extraction

INTRODUCTION

Particle Swarm Optimization (PSO) algorithm is motivated by the social behavior of organisms, such as bird flocking and fish schooling. As an important method of optimizing, PSO algorithm has been successfully applied to identification, ANN fields, and so on (Cristian, 2003; Clerc and Kennedy, 2002).

Compared to other optimizations, PSO algorithm is better at having less parameter to adjust and bigger velocity on convergence. But it is easier to stop at the local optima especially for the multi-optima questions. In order to improve the ability of global optimization, a lot of research works have been done (Li *et al*., 2005; Yan and Han-ming, 2010; Huang and Xiao-ping, 2006). This paper proposes an improved PSO algorithm. Via fourth order cumulant matching, this new method is applied to seismic wavelet estimation.

IMPROVED PSO ALGORITHM

PSO algorithm is initialized with a population of random solutions named particles. A swarm consists of a set of particles moving around the search space, each representing a potential solution. Each particle has a position vector (xi = (xi1, xi2, …, xid)) and a velocity vector (vi = (vi1, vi2, …, vid)). In each generation, the velocity of each particle is updated to their best encountered position and the best position encountered by any particle. The position and the velocity change as the following formula:

$$v_{id}(t+1) = w*v_{id}(t) + cl*rl* (p_{id}(t) - x_{id}(t) + c2*r2*(p_g(t) - x_{id}(t)) \quad (1)$$

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1) \quad (2)$$

The position at which the best fitness encountered by the particle is pi = (pi1, pi2, …, pid) and the best particle in the swarm is pg. The parameters c1 and c2 are acceleration co-efficient. r1 and r2 are two random values, uniformly distributed in [0, 1] and w is called as inertia weight, which controls the influence of the previous velocity on the new velocity.

The two parameters are usually set to constant values. But here the acceleration co-efficient are set as a linearly decreasing time varying function:

$$c1 = c1_{start} - k*(c1_{start} - c1_{end})/gen \quad (3)$$

$$c2 = c2_{start} - k*(c2_{start} - c2_{end})/gen \quad (4)$$

with a large value of c1 and a small value of c2 at the beginning, particles are allowed to move around the search space. A small value of c1 and a large value of c2 allow the particles converge to the global optima in the latter part of the optimization.

We bring in a differential evolution to yield a set of temporal particles xt. Each member of the xt set is compared with the corresponding father member, so the perturbed version replaces the father if it has a better fitness value:

$$xt(i,j) = x(pi,j) + r*(x(p2,j) - x(p3,j)) \quad (5)$$

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where r is a random between 0 and 1, p1, p2, p3 is random between 1 and gen, x is the position of the particle before the perturbation, while xt is the position of the particle after the perturbation, $1 \leq j \leq d$.

In this stage, perturbation is applied to every particle to yield a set of temporal particles. The new particles are compared to their father members, and the better ones wins.

A random perturbation is applied to some particles with the probability 1/d (d is defined as the dimension of the particles).

If r $\leq$1/dxt(i,j) = rand*(u-l)+1 % to yield a new particle;
else xt(i,j) = x(i,j) % the particle doesn't change;
End

where u and l are the upper and lower position values the particles can be allowed.

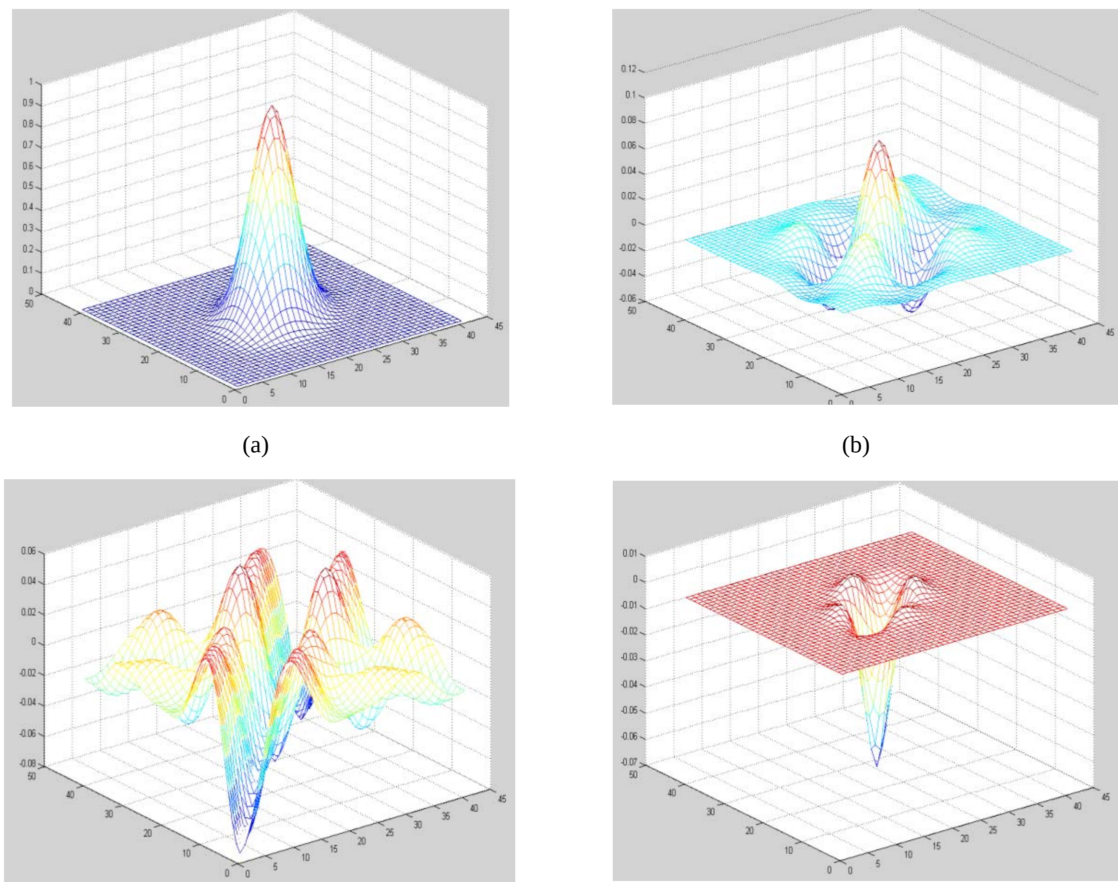
when any particle escapes, its position will be redefined. It changes as follows:

if (x_{id} < l) x_{id} = u-mod(l - x_{id}, u - l)
if (x_{id} < l) x_{id} = l - mod(x_{id} - u, u-l)

The modulus operator is 'mod'. Under this condition, the particles which have escaped will fly to the possible solutions and this betterment also keeps the population diversity. The above two perturbations we proposed is aimed to keep diversity and find promising results.

THE ESTIMATION OF WAVELET

Seismic wavelet extraction is one of the important long-standing research works in seismic data processing. Nowadays, there are mainly two kinds of methods to estimate seismic wavelet (Danilo and Tadeusz, 1996; Gregory, 1993). The first method has the limit that the reflectivity series must be known. The second method has the hypothesis that the reflectivity series is in some certain form, such as the cumulant of the reflectivity series is a multidimensional spike at zero lag.



(a) (b) (c) (d)

Fig. 1: (a) Fourth-order moment of a Ricker wavelet (b) 3-D Parzen window function(c) fourth-order cumulant function of a trace (d) after the application of a 3-Parzen window

The high-order cumulant method gives the characteristics of the signal in the higher order sense and is sensitive to amplitude and phase. Using high-order cumulant to extract wavelet becomes one of the hot research problems in recent years.

The first problem by using PSO algorithm to solve seismic wavelet estimation is to establish the cost function. The seismic trace is known and the reflectivity is a non-Gaussian, independent, and symmetrically distributed random process. By applying fourth-order cumulant to the seismic trace model, the fourth-order moment of the wavelet, within a scale factor, equals the fourth-order cumulant of the trace. So we can define the cost function in a minimum-squared error sense as follows:

$$\phi = \sum_{\tau_1=0}^{q}\sum_{\tau_2=0}^{n}\sum_{\tau_3=0}^{\tau_2}[c_{4x}(\tau_1,\tau_2,\tau_3)-\gamma_{4e}M_{4h}(\tau_1,\tau_2,\tau_3)]^2 \tag{6}$$

where, $0 \le \tau_1 \le q$, $0 \le \tau_2 \le \tau_1$, $0 \le \tau_3 \le \tau_2$, q is the length of the wavelet, $c4x(\tau_1, \tau_2, \tau_3)$ is fourth-order cumulant function of seismic trace, $\gamma 4e$ is the kurtosis of the reflectivity series, $M4h(\tau_1, \tau_2, \tau_3)$ is the fourth-order moment of the wavelet which will be extracted.

Since in practice neither the cumulant of the noise is zero nor the cumulant of the reflectivity series is a multidimensional spike at zero lag, the estimated wavelet moment obtained from equation is a distorted version of the true wavelet moment. To improve the estimation, we found it is very useful to apply a 3-D smoothing-taper window to the trace cumulant. We define a 3-D Parzen window $a(\tau 1,\tau 2,\tau 3)$, then the cost function (6) becomes as follow:

$$\phi = \sum_{\tau_1=0}^{q}\sum_{\tau_2=0}^{\tau_1}\sum_{\tau_3=0}^{\tau_2}[c_{4x}(\tau_1,\tau_2,\tau_3)a(\tau_1,\tau_2,\tau_3)- \gamma_{4x}M_{4h}(\tau_1,\tau_2,\tau_3)]^2 \tag{7}$$

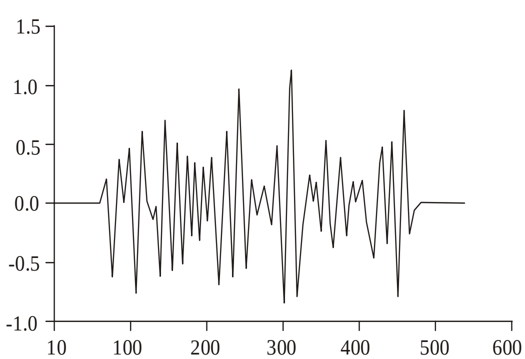


Fig. 2: Parts of the synthetic seismic trace

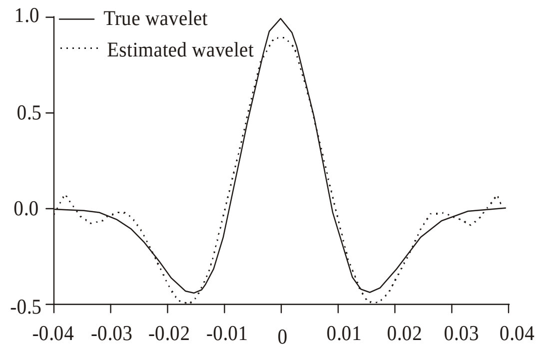


Fig. 3: The extracted Ricker wavelet

NUMERICAL EXPERIMENTS

Figure 1 show the fourth-order moment of a Ricker wavelet and the fourth-order cumulant of a synthetic trace by applying the window within a scale factor.

From the above Fig. 1, 2 we can see that adding 3-D Parzen window to the trace cumulant is quite important. It is obvious that the fourth-order moment of the wavelet within a scale factor equals the fourth-order cumulant of the trace by applying the window.

The results by using the improved PSO algorithm is shown in Fig. 3. The selection of the parameters is as follows: population n = 25; particle dimension d = 41; the total iteration gen = 50; the utter limit u = 1.0, while the low limit l = -0.5; the maximum velocity vmax = 0.7, the minimum velocity vmin = -0.7; the acceleration co-efficient start value c1start = 2.5, c2start = 1.5 and the end value c1end = 1.5, c2end = 2.5.

In practice, the seismic trace is finite and the reflectivity can't satisfy the hypothesis, so the extracted wavelet is right in some allowable precision.

CONCLUSION

An improved particle swarm optimization is presented in the paper. The details of the new method are described and implemented. A linear time-varying acceleration co-efficient and two mutations are proposed. So at the early age, the particles can wander through the entire search space without clustering around the local optima. The new method is applied to seismic wavelet estimation via fourth order cumulant matching. The experiment results show that it is feasible to solve the wavelet estimation.

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