Global Congress on Intelligent Systems

10.1109/GCIS.2009.464

A Dolphin Partner Optimization

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Abstract

In this paper, based on the bionic study on dolphin, a philosophy of dolphin Partner Optimization (DPO) was formulated and a so-called "Nucleus" was introduced to predict the best position according to the positions and fitness of the team members. After that, we test the DPO algorithm on several benchmark functions and the experiment result show it has rapid and niche character and good adaptability for different objective functions.

Keywords: Dolphin Partner Optimization; Nucleus; PSO; niche

1. Introduction

The Particle Swarm Optimization (PSO) algorithm is an evolutionary optimization technique originally introduced by Kennedy and Eberhart in 1995[1]. It has many properties, including simplicity of implementation, scalability in dimension, and good empirical performance [2-3]. It has been compared to GA and other evolutionary algorithms and showed its superiority [4-5].

In the standard PSO model, each individual is treated as a volume-less particle in the D-dimensional space. The particles move according to the following equations:

$$v_i(t+1) = wv_i(t) + c_1 r_1 (p_i - x_i(t)) + c_2 r_2 (p_g - x_i(t)) \tag{1}$$
$$x_i(t+1) = x_i(t) + v_i(t+1)$$

The fly of particles is promoted by its $pbest$ and $gbest$ information [6]. But this promotion is directivity indistinct; the particles may wander around the valley or peak. On the other hand, the particles exchange only global best positions, the fitness is ignored.

This paper presents a new approach to particle motion that significantly speeds the search for optima while simultaneously remains the global convergence capability.

2. Dynamic of dolphin

Dolphin is one of the great creatures with great intellectual and physical capacities, whose capacities to think and move at an astounding rate puzzle those who study their behaviors. Dolphins possess something that makes them different from the other entire sea creature.

Dolphins use sound to help them find their way, look for their food and talk with each other. They also find their prey by cooperation. Here are some most intelligent principles of the seeking activity:

A. **Cluster**: A dolphin will look for its neighbors and select some buddy as his partner. All his partners and himself form a self-organization team, which is a virtual dynamic team at that moment. Each dolphin will do the same things respectively, so each dolphin will has his own team.

B. **Role recognized**: A dolphin should evaluate himself comparing to the other partners in his team, then he should determined to play a leading role or act as just an ordinary member of the team. Normally the one with the best fitness turns into the leader of the team.

C. **Communication**: A dolphin should communicate with each of his partners from his team by exchanging information. The partner dolphin may belong to another team, and has another team's fitness. All the "team best position" coming from the whole partners is notified to the dolphin, he should remember the best one of them as a reference named "neighbor team best position". So each dolphin can mark their "neighbor team best fitness" by exchanging information with his partner. The communication can be executed many times, and the best fitness information of other dolphin far away can be spread around the groups.

D. **Leadership**: the leader dolphin of his team should do much challenging work to fulfill its mission. He should analyze the position and fitness of everyone in the team and predicate the most available position and try to evaluate it.

978-0-7695-3571-5/09 $25.00 © 2009 IEEE
DOI 10.1109/GCIS.2009.464

E. **Follow**: the ordinary dolphin of his team has only one thing to do, that is, just following the step of pioneers. He should swim under the directive of both the "team best position" and the "neighbor team best position".

3. Prediction of nucleus

Generally speaking, a continuous function can be divided into several sections, which will be a convex function or concave function. Many functions also have a convexity feature or concavity feature at large.

Concerning about the maximum and minimum, two types of point O's nucleus are introduced to present different positions:

I. Heavy Nucleus: the most likely position to achieve the minimum values
II. Light Nucleus: the most likely position to achieve the maximum values

Another two types of nucleus are also defined as:

I. Inner Nucleus: the nucleus among the inner space of positions of team members
II. Outer Nucleus: the nucleus among the outer space of positions of team members

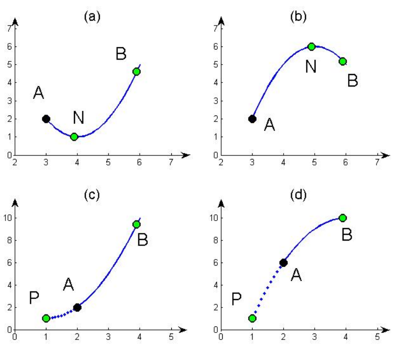

Fig. 1. One-dimensional function,
A is a particle and B is its neighbor.

Fig.1 demonstrates the nucleuses for one-dimensional functions with ideal convexity feature. For (a) and (b), N represents the inner nucleus, for (c) and (d), "P" represents the outer nucleus.

The $f'_{(H,L)}(x_i)$ (namely $f'_H(x_i)$ or $f'_L(x_i)$) is the transfer function fitness with $f'_{(H,L)}(x_i) > 0$ and $x_i (i = 1, 2...n)$ are the team dolphin positions. The transfer function should be carefully chosen to get the most approximation. For minimum functions with positive values, the transfer function can be chosen as

$$f'_H(x) = f(x)$$
$$f'_L(x) = \frac{1}{f(x)} \qquad (2)$$

For minimum function without matching this limit, simple instead transfer functions can be selected for heavy nucleus $N_H(k)$ and light nucleus $N_L(k)$:

$$f'_H(x) = f(x) - f_{gbest}(x)$$
$$f'_L(x) = \frac{1}{f(x) - f_{gbest}(x)} \qquad (3)$$

The $f_{gbest}(x)$ is the least fitness value for all dolphins. It is noted that some other nonlinear sigmoid function can also be used for better approximation based on the problem to resolve.

The outer nucleus may be evaluated by:

$$P(k) = N_L(k) \pm \log\left(\frac{1}{\mu}\right) * \left(N_L(k) - N_H(k)\right) \qquad (4)$$

Where μ is a random value in $(0,1)$.

It is noted there are many other methods to estimate the inner and outer nucleus.

4. The DPO algorithm

The Dolphin Partner Optimization (DPO) algorithm can be summarized here:

Initialize dolphin population: random x_i
Do
For each dolphin
    Find out its partners and form a virtual team
    Find out its role in his team
    Exchange team best position within partners
End For
For each dolphin
    Calculate the inner nucleus and outer nucleus
    If this dolphin is leader of his team
        If fitness of inner nucleus is better
            $x_i(t+1)$ = inner nucleus
        Else
            $x_i(t+1)$ = outer nucleus
        End
    Else
        Update $x_i(t+1)$
Until termination criterion is met

4.1. Partner selection

A dolphin often chooses a few friends nearby him as his partners. For each dolphin k , calculate the $dist(k, j)$, ($j = 1..n$) between other dolphins. Then $Ldist$ is sorted $dist$ order by fitness from best to worst.

The $sample$ parameter is a random value related to iteration, it should be decreased step by step.

$$sample = (\lambda_{\max} - \lambda_{\min}) * (MaxIter - t) / MaxIter + \lambda_{\min} \quad (5)$$

The stretch parameter $beta$ can be set as

$$beta = \beta * (teamsize / popsize) \quad (6)$$

to control the furthest partner.

$Team(k,1)$ is always the dolphin k himself, and $Team(k,2)$ to $Team(k,teamsize)$ are his partners.

4.2. Roles

Once the team of this dolphin is setup, the $tbest$ can be selected, which means the best position of all the dolphins in the team. If the dolphin himself is the $tbest$, he is growing up to be the leader of the team.

4.3. Communication

After each dolphin has build up his team, he can communicate with the team members to get the better position and fitness value. This information exchange can be performed for several times, and the better dolphin can be well-know by his partners. Every dolphin will has his own $nbest$, the best position among the neighbor teams of his partners.

4.4. Swim forward the direction

As an ordinary member of his team, the positions updated by function:

$$x_i(t+1) = x_i(t) + c_1 r_1 (p_{ti} - x_i) + c_2 r_2 (p_{ni} - x_i) \quad (7)$$

The p_{ti} is $tbest$ position of the dolphin i , and p_{ni} is $nbest$ position of dolphin i .

5. The result of experiments

To test the performance of the Dolphin Partner Optimization, seven benchmark functions are used here for comparison with SPSO and GA.

The first function is Sphere function described by:

$$f(x) = \sum_{i=1}^{n} x_i^2 \quad (8)$$

The second function is Rosenbrock function described by:

$$f(x) = \sum_{i=1}^{n-1} \left[100 \left(x_i^2 - x_{i+1} \right)^2 + \left(x_i - 1 \right)^2 \right] \quad (9)$$

The third function is the generalized Rastrigin function described by:

$$f(x) = 10n + \sum_{i=1}^{n-1} \left(x_i^2 - 10\cos(2\pi x_i) \right) \quad (10)$$

The fourth function is generalized Griewank function described by

$$f(x) = \sum_{i=1}^{n} \frac{x_i^2}{4000} - \prod_{i=1}^{n} \cos\left(\frac{x_i}{\sqrt{i}} \right) + 1 \quad (11)$$

The fifth function is De Jong's function (no noise) described by:

$$f(x) = \sum_{i=1}^{n} 5i * x_i^2 \quad (12)$$

The sixth function is Shaffers function described by

$$f(x) = 0.5 + \frac{\left(\sin\sqrt{x^2 + y^2} \right)^2 - 0.5}{\left(1.0 + 0.001\left(x^2 + y^2 \right) \right)^2} \quad (13)$$

To compare with other evolution algorithm, we take standard particle swarm optimization (SPSO) and Generic Algorithm (GA) . In order to investigate the scalability of algorithm, different dimension of 10 and 30 is test respectively .The population size is set to 20. Generation is set as 1000 and 2000 corresponding to the dimension of 10 and 30.

Table I. Best values for test function

D	func	iter	SPSO	DPO	GA
30	sphere	1000	3.5013	0.0002	0.0001
		2000	1e-11	1e-8	1e-5
	rosenbrock	1000	4350.9	1045.2	17178
		2000	58.5634	563.4867	17164
	rastrigin	1000	155.5259	62.6975	66.8908
		2000	45.4697	44.8839	66.9173
	griewank	1000	5.4795	0.3442	0.2754
		2000	0.0251	0.0247	0.2429
	Dejong	1000	73.8763	0.0289	0.0142
		2000	1e-10	1e-8	0.0126
		1500	1e-36	1e-37	1e-6
	rosenbrock	1000	3.4546	5.0906	4654.6
	rastrigin	1000	4.9252	3.7808	18.7140
	griewank	1000	0.1082	0.1398	0.4777
	De jong	1000	1e-22	1e-21	1e-5

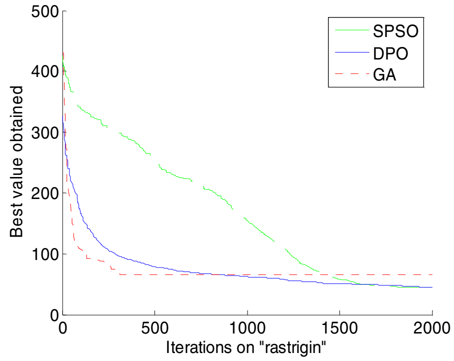

Fig.2 Rastrigin function test

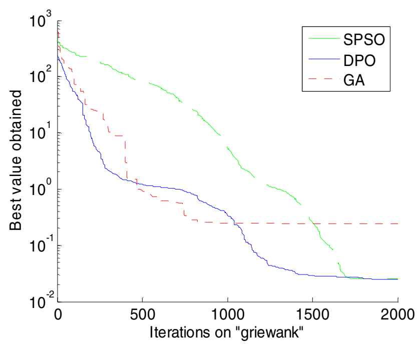

Fig.3 Griewank function test

For SPSO, c1=c2=2. For GA, the cross rate is 0.8 and the mute rate is 0.4.The parameter of DPO is: $sample$ decreases form 0.9 to 0.4 linearly, and $\beta = 2$ in formula (6).

Another test function is introduced here to present the ability of DPO, the Branin function described by:

$$f(x) = \left(x_2 - \frac{5}{4\pi^2} x_1^2 + \frac{5}{\pi} x_1 - 6 \right)^2 + 10\left(1 - \frac{1}{8\pi}\right) * \cos(x_1) + 10 \qquad (14)$$

To find out all these minima, 50 population and 100 iterations are set, and the team size is 3. The success of the niche algorithm depends on the proper initial distribution of particles throughout the search space[7] . To ensure uniform distribution, $Faure$ -sequences were used to generate initial particle positions (as described in [8]). $Faure$ -sequences are distributed with high uniformity within an n -dimensional unit cube.Fig.2 shows that the DPO can find the minima rapidly by its niche character.

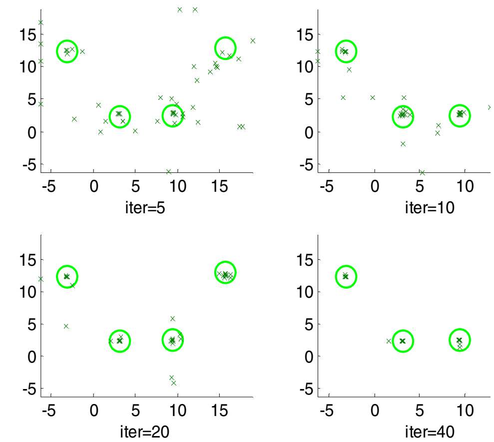

Fig.4 Iterations on Branin function

6. Conclusion

The DPO can achieve fairly better value in the beginning several steps and breakthrough the local minimum while GA always lost in. It is shown that in the end of iterations particles of SPSO system are able to escape the trap of the sub-optima more frequently than that of DPO. It should be noted that much research should do to find a more effective method to predict the inner and outer nucleus. The comparison and potential combination of DPO with other improvements is part of ongoing research and will be a subject of future work.

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