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Improving the Performance of Particle Swarm Optimization with Diversive Curiosity

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Abstract— **How to keep a balance between exploitation and exploration in Particle Swarm Optimization (PSO) for efficiently solving various optimization problems is an important issue. In order to handle premature convergence in PSO search, this paper proposes a novel algorithm, called Particle Swarm Optimization with Diversive Curiosity (PSO/DC), that introduces a mechanism of diversive curiosity into PSO for preventing premature convergence and ensuring exploration. A crucial idea here is to monitor the status of behaviors of swarm particles in PSO search by an interior indicator, and when swarm particles dropped into local minimum, they will be spontaneously reinitialized to start on finding other new solutions in search space. Applications of the proposal to a 2-dimensional optimization problem well demonstrate its effectiveness. Our experimental results indicate that the performance (90%) of the proposed method is superior in terms of success ratio to that (60%) of the PSO model optimized by EPSO.**

Keywords: particle swarm optimization, evolutionary particle swarm optimization, temporally cumulative fitness function, diversive curiosity, premature convergence

1 Introduction

Although the mechanism of the original PSO is simple with only three parameters to adjust, through the interactions of swarm particles, it can provide better results compared with other methods such as machine learning, neural network learning and genetic computation [3, 6, 7, 10]. However, how to appropriately determine the values of parameters in PSO models for efficiently solving various optimization problems is an important and attractive challenging problem.

Many researchers paid much attention to the above problem, and proposed various algorithms for coping with it. To systematically estimate a proper parameter set in PSO model, Meissner et al. proposed an Optimized Particle Swarm Optimization (OPSO) method as an extension of CPSO, which uses PSO for meta-optimization of PSO heuristics [8, 9]. Zhang et al. proposed Evolutionary Particle Swarm Optimization (EPSO), in which the Real-coded Genetic Algorithm with Elitism strategy (RGA/E) is used for estimating appropriate values of parameters in PSO [15].

Although the PSO model optimized by EPSO has superior performance over other methods [1, 4, 11], the issue of balancing between exploitation and exploration in PSO search has not been completely solved. It still tends to converge to local minimum, i.e., premature convergence, in solving multimodal optimization problems. It seems to be necessary of introducing not only new variants of PSO but also new strategies which still execute exploration at same time for dealing with the problem [7]. How to make the swarm particles to succeed in balancing between exploitation and exploration in PSO search for efficiently solving various optimization problems is authors' motivation.

So far, there are many methods and strategies, such as non-global best neighborhoods increase exploration, and local searches to perform exploitation for problem solving [13, 14]. They are effective in solving multimodal optimization problems, but the mutual fault of them exists at great expense with heavy composite computation for balancing between exploitation and exploration in PSO search.

To overcome the above difficulty, this paper proposes a novel algorithm, called Particle Swarm Optimization with Diversive Curiosity (PSO/DC), that introduces a mechanism of diversive curiosity into PSO to prevent premature convergence and ensure exploration in PSO search for improving performance of PSO.

Curiosity is a concept on stimulus/sensation seeking for humans and animals in psychology. D. Berlyne divided curiosity into two types: *diversive* and *specific* [2]. Diversive curiosity is a general tendency to seek novelty, to take risks, and to search for adventure. Specific curiosity is a tendency to investigate a specific object or problem in order to understand it thoroughly.

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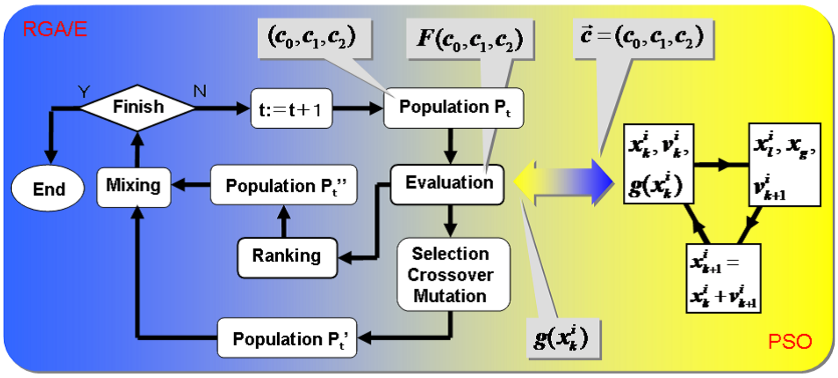

Figure 1: Flowchart of EPSO

Diversive curiosity is applied to PSO search, since it can give swarm particles engage in continually seeking novelty etc. in order to relieve boredom or to raise arousal [12]. As an individual part of swarm intelligence used in PSO/DC, how to realize the diversive behavior of swarm particles in PSO search by engineering technique becomes a key point [5].

Specifically, in this paper we suppose that the potential mechanism of diversive curiosity in psychology can be divided into the following two parts for fulfillment: One is to monitor the status of behaviors of swarm particles in PSO search by an interior indicator for judging whether they dropped into local minimum or not. The other is to spontaneously reinitialize the swarm particles based on receiving the responsive value of the indicator for relieving boredom or raising arousal to start on finding other new solutions in search space.

Based on the above, this is a less expensive and practical algorithm by implementing PSO just with the indicator, no more complex computations. We effectively utilize the function of indicator on preventing premature convergence, and to ensure exploration in PSO search for efficiently solving various optimization problems, and expect that the superior performance of PSO/DC can be secured by enhancing the initialization frequency of PSO in the fixed search interval.

Obviously, the performance of PSO/DC will be directly reflected by the performance of the used PSO model. At this point, how to obtain a PSO model with superior performance, and apply it into PSO/DC for efficiently finding an optimal solution are also an important part of construction of the proposal. In order to secure the performance of PSO/DC, we adopt the parameter setting by EPSO to generate the PSO model.

The rest of the paper is organized as follows. Section 2 describes the mechanism of EPSO. Section 3 proposes a novel algorithm, PSO/DC. Section 4 discusses the results of computer experiments applied to a 2-dimensional optimization problem, analyzes the characteristics of PSO/DC, and compare with the performance of other methods. Section 5 gives conclusions and discussions.

2 EPSO

The original PSO is modeled by particles with position and velocity as follows.

$$\boldsymbol{x}_{k+1}^i = \boldsymbol{x}_k^i + \boldsymbol{v}_{k+1}^i \quad (1a)$$

$$\boldsymbol{v}_{k+1}^i = c_0 \boldsymbol{v}_k^i + c_1 \boldsymbol{r}_1 \otimes (\boldsymbol{x}_l^i - \boldsymbol{x}_k^i) + c_2 \boldsymbol{r}_2 \otimes (\boldsymbol{x}_g - \boldsymbol{x}_k^i) \quad (1b)$$

where $\boldsymbol{x}_k^i$ and $\boldsymbol{v}_k^i$ denotes the position and velocity of the ith particle at time k, respectively. c_0 is an inertial factor, c_1 is an individual confidence factor, and c_2 is a swarm confidence factor, $\boldsymbol{r}_1, \boldsymbol{r}_2$ are random vectors in which each component is uniformly distributed in the range [0,1], and $\otimes$ is an element-by-element operator for vector multiplication. $\boldsymbol{x}_l^i (l = arg \max_{k=1,2,\cdots} \{g(\boldsymbol{x}_k^i)\}$, where $g(\boldsymbol{x}_k^i)$ is the fitness value of the ith particle at time k) is the local best position, lbest, of the ith particle up to now, and $\boldsymbol{x}_g (g = arg \max_{i=1,2,\cdots} \{g(\boldsymbol{x}_l^i)\})$ is the global best position, gbest, of the swarm particles, respectively.

EPSO provides a new paradigm of meta-optimization for model selection to swarm intelligence, which can systematically estimate a proper parameter set of PSO to generate a PSO model with superior performance [15]. Figure 1 illustrates the flowchart of EPSO.

Specifically, the procedure of EPSO is composed of two parts: One is to implement a Real-coded Genetic Algorithm with Elitism strategy (RGA/E) applied to simulating the survival of the fittest among individuals over generations for solving real-valued optimization problems. While the PSO finds a solution to a given optimization problem, it is used to optimize the values of parameters in the PSO with on-line evolutionary computation. The other is to implement PSO. The PSO with the values of parameters created by RGA/E is expected to achieve higher fitness than others.

For obtaining a PSO model with superior performance, the following temporally cumulative fitness of the best particle is used in EPSO.

$$F(c_0, c_1, c_2) = \sum_{k=1}^{K} g(\boldsymbol{x}_k^b)\big|_{c_0,c_1,c_2} \qquad (2)$$

Here, $\boldsymbol{x}_k^b$ ($b = arg\,max_{i=1}^{P}\{g(\boldsymbol{x}_k^i)\}$, P: the number of swarm particles) is the position of the best particle at time k, and K is the maximum number of iterations in PSO.

In our research, it has been demonstrated that the PSO model optimized by EPSO with the fitness function, F, has unique performance in keeping the balance between exploitation and exploration in PSO search [16].

3 The proposal, PSO/DC

3.1 Indicator for Diversive Curiosity

It has been identified that diversive curiosity occupies a critical position at the crossroad of cognition and motivation. The partition of them into different behaviors is the basis of the regional evaluation of motivation.

For achieving the potential mechanism of diversive curiosity by engineering technique, the following indicator, y_k, is designed to represent the critical point which determines the time for relieving boredom or raising arousal to find other new solutions in PSO search.

$$y_k(L, \varepsilon) = max\Big(\varepsilon - \sum_{l=1}^{L} \frac{|g(\boldsymbol{x}_k^b) - g(\boldsymbol{x}_{k-l}^b)|}{L},\ 0\Big) \qquad (3)$$

Here L is a period of judgment, ε is a positive tolerance parameter marking a limit of satisfaction for understanding the solution, $\boldsymbol{x}_k^b$. In other words, when the responsive value of the indicator, y_k, is great than zero, the cumulative variation of the best particle, $\boldsymbol{x}_k^b$, is less than the parameter, ε, at time k for cognition. This meaning here is that the swarm particles don't content themselves with the known solution, $\boldsymbol{x}_k^b$, until now for cognition, and start on finding other unknown new solutions in search space for motivation.

Just as the above interior indicator well provides the imformation to swarm particles, lead them to whether pursue other new solutions more in PSO search or not for realizing diversive curiosity by engineering technique. It is the reason for naming this to be diversive behavior of swarm particles realized by successfully setting up the interior indicator.

3.2 Procedure of PSO/DC

Based on the above, we introduce the above indicator to PSO for constructing the program of PSO/DC, which perform the mechanism of diversive curiosity. The procedure of PSO/DC is implemented as follows.

Begin
  Set the number of maximum search, K;
  Set k=0, d=-1;
  Set gbest set to empty;
  While k<=K **Do**
    If k=0 or d=1 **Then** initialize swarm;
    Else
      For each particle
        Calculate position and velocity;
      End For
      Update each local best particle;
      Update global best particle;
    End If
    Calculate the value, y_k, of indicator;
    If y_k<=0 **Then** d=y_k;
    Else d=1 **Do** add global best to gbest set;
    End If
    k=k+1;
  End While
  Select the best result from gbest set;
End

It is crystal clear that since the indicator just fills the role of judging whether the swarm particles dropped into local minimum in PSO search or not, the structure of PSO/DC is very simple, i.e., the mechanism of diversive curiosity is realized by the command, "If-Then", and the reinitialization of swarm particles in the procedure. Note that the proper parameter set of PSO estimated by EPSO is used in PSO/DC for securing the superior performance in search.

4 Computer Experiments

4.1 Experimental Conditions

Computer experiments are carried out for investigating the characteristics of EPSO with fitness function, F, and the performance of PSO/DC to solve the given 2-dimensional optimization problem in Figure 2. The search space is 60×60 ($x_{max}=30$), and the value of the best fitness is about 0.4.

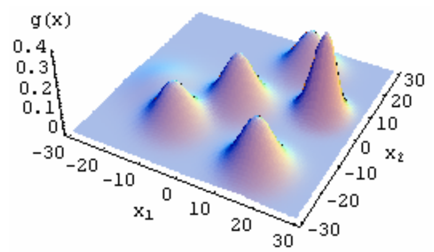

Figure 2: Optimization problem

Table 1 gives the major parameters in EPSO for estimating appropriate values of parameters in PSO.

Table 1: The major parameters used in EPSO.

Items	Parameters
the number of individuals	M = 100
the number of generation	G = 20
the number of superior individuals	$s_n = 1$
roulette wheel selection	–
probability of BLX-2.0 crossover	$p_c = 1.0$
probability of random mutation	$p_m = 1.0$
The number of particle	P = 10
The number of iterations	K = 400
The maximum velocity†	$v_{max} = 20$

† Note that the constant, v_{max}, is used to arbitrarily limit the velocity of each particle in search.

4.2 Results for EPSO

Table 2 shows the resulting parameter values of PSO by EPSO for the fitness function, F [1]. It is to be noted that the values of parameters in PSO are estimated under the limitary condition, i.e., the parameters, c_0, c_1, and c_2, are not negative. We observed that the EPSO generates 3 types of models which all can solve the given optimization problem, regardless of the different frequency they have within superior 20 trials. These results clearly indicate that the swarm confidence factor, c_2, is always included in the models with superior performance, and plays an essential role in finding an optimal solution to the optimization problem.

Table 2: Estimated parameter values in PSO and the frequency of each type of the resulting models.

Fit-ness	Mo-del	Parameter c_0	c_1	c_2	Fre-quency
	a	0	0	3.26±1.35	45%
	b	0	1.26±0.90	3.33±1.07	30%
F	c	-	-	-	0%
	d	0.70±0.30	0.64±0.36	2.86±1.84	25%

The aim of EPSO is to find a proper parameter set that provides the PSO with reasonable exploration and convergence capability for efficiently solving a give optimization problem. We assume that the larger the average of fitness is, the better the performance of a model is. Under this assumption, the performance of each PSO model in Table 2 can be easily determined.

Figure 3 illustrates the frequency distribution of fitness for each PSO model runs. And Table 3 gives the mean and the standard deviation regarding the obtained frequency distribution of fitness the gbest particle has for each PSO model runs.

[1]Computing environment: Intel(R) Xeon(TM); CPU 3.40GHz; Memory 2.00GB RAM; Computing tool: Mathematica 5.2; Computing time: about 3 min.

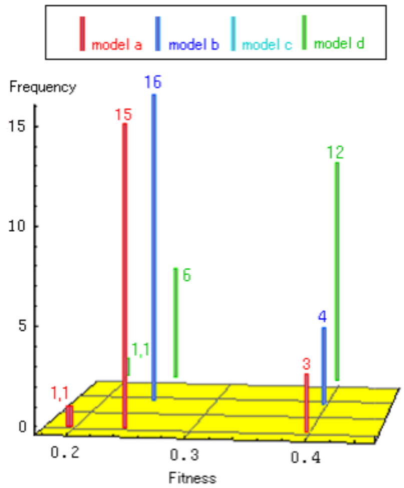

Figure 3: Frequency distribution of fitness values for each PSO model.

Table 3: The mean and the standard deviation of fitness for each model.

	model a	model b	model c	model d
Fitness	.267±.058	.280±.061	–	.335±.082

Firstly, by comparing the mean values of fitness for each PSO model, we can confirm that the PSO model in type d has higher performance than other models in exploration, and the following relationship of search performance for the resulting models is provided depending on the order of the mean values.

$$\text{model } d \succ \text{model } b \succ \text{model } a$$

Secondly, we use the objective criterion [16] representing the swarm particles found a near-optimal solution and converge on it by the equation, $\forall k \geq k_{max},\ \ g(\boldsymbol{x}_k^b) - \bar{g}_k \leq \tau$ ($\bar{g}_k$: average fitness of the swarm particles; τ: a positive tolerance parameter) to evaluate the convergence property of an entire swarm. When the parameter $\tau = 0.03$ is set, the mean of maximum time-step of the PSO model in type d is $k_{max} \cong 82$. The result indicates that the PSO model in type d has stronger convergence in exploitation, too.

4.3 Results for PSO/DC

The resulting PSO model in type d are adopted in PSO/DC. The parameters of the indicator in PSO/DC, $\varepsilon = 0.001$ and $L = 40$ time-step, are used in the below experiments.

Figure 4 illustrates a variation of the fitness of the gbest particle in a search process of PSO/DC. We can clearly see that the swarm particles were reinitialized three times during the search process. Based on the function of diversive curiosity, indeed it provided the chance for the

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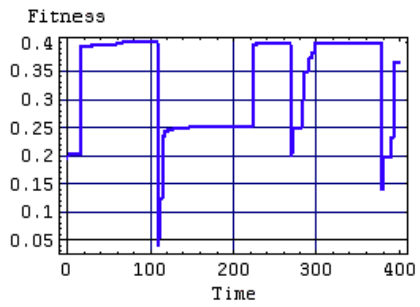

Figure 4: A variation of the fitness of the best particle in a search process of PSO/DC

PSO model optimized by EPSO with bigger probability to find an optimal solution (i.e., global solution) in the search space.

Table 4 gives the resulting performance for each method, and Figure 5 illustrates the distribution of the obtained results for each method.

Table 4: The performance for each method for 20 trials.

	PSO	PSO/DC$^\flat$	EPSO	PSO/DC$^\sharp$
success ratio	40%	80%	60%	90%

$^\flat$ The parameter set of the original PSO is used to PSO/DC.
$^\sharp$ The parameter set estimated by EPSO is used to PSO/DC.

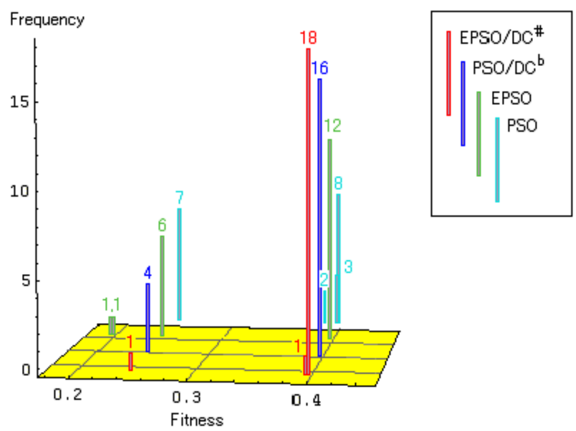

Figure 5: Distribution of the obtained results for each method.

Comparison with the frequency of achieving the global solution in Figure 5 for each method, we observed that the performance of the proposed method is greatly improved by implementing the procedure of PSO/DC than that by implementing PSO or EPSO. The increasing ratio in finding the global solution is 100% up to PSO, and 50% up to EPSO, respectively. It sufficiently reflects the mechanism of diversive curiosity plays an important role and has wonderful function in search.

Based on the contribution of the mechanism of diversive curiosity to the exploitation and exploration in PSO search, the distribution region of the particles is also relatively extended. For the comparison of the distributions, both of the obtained results corresponding to EPSO and PSO/DC$^\sharp$ are shown in Figure 6. We can clearly see that the tracks of the swarm particles are not only around each local solution shown in Figure 6(a), but also around other space shown in Figure 6(b).

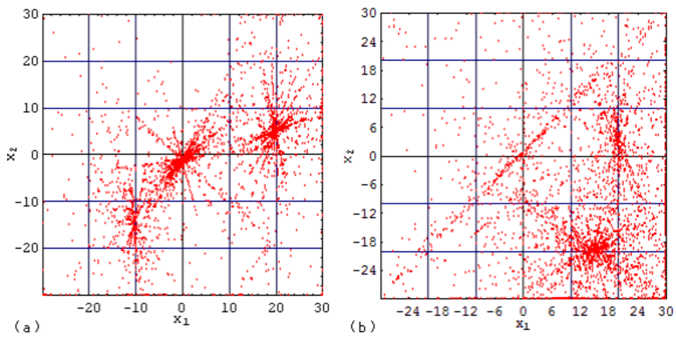

Figure 6: Distribution of the obtained results for each method. (a) EPSO, (b) PSO/DC$^\sharp$.

The results indicate that the rise of frequency of the appearance of particles in the unit space. This effect reflects that PSO/DC well keeps the balance between exploitation and exploration in PSO search for efficiently solving the given optimization problem. It leads the performance improvement of the PSO model optimized by EPSO in the search efficiency.

5 Conclusions and Discussions

We have proposed a novel algorithm, Particle Swarm Optimization with Diversive Curiosity, PSO/DC, that successfully introduces a mechanism of diversive curiosity into PSO. The crucial idea here is to monitor the status of behaviors of swarm particles in PSO search by an interior indicator for preventing premature convergence and ensuring exploration in PSO search as a method for realizing the mechanism of diversive curiosity in psychology. The algorithm of PSO/DC can be considered as a relative low expense and practical algorithm without more complex computation except just monitoring the status of behaviors of swarm particles in PSO search and reinitializing swarm particles.

By the marked function of diversive curiosity, PSO/DC can keep the balance between exploitation and exploration in PSO search. Applications of the proposed method to a 2-dimensional optimization problem well demonstrate its effectiveness. Our experimental results indicate that the performance (90%) of the proposal is superior in success ratio than the performance (60%) of the PSO model optimized by EPSO.

Theoretically, PSO/DC is effective at enhancing the performance of different variants of PSO, and is suitable to solve various optimization problems. And, we are looking into applying PSO/DC in dynamic environments.

Even though better experimental results have been obtained, only a 2-dimensional optimization problem was carried out. It is left for further study to apply the proposal to benchmark optimization problems and complex application problems in the real-world.

Although the procedure of PSO/DC is simple to implement and has only two parameters to adjust, the performance of PSO/DC deeply depends on the parameter setting. Specially, how to determine the value of the period of L time-step is very important.

In general, diversive curiosity may lead to exploration, but it also creates anxiety. In other words, the satisfaction to know current information is not only decided by the object's character but also decided by the performance of the adopted PSO model itself. From the viewpoint of search efficiency, in general, a short period of L time-step is better for quickly dealing with premature convergence in PSO search for exploration. But the search will becomes insufficient in exploitation when this expires in the shortness. It is left for further study to investigate the influence of the factor, L, to the performance of PSO/DC.

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