Particle Swarm Optimization with Diversive Curiosity — An Endeavor to Enhance Swarm Intelligence

Hong Zhang, Member IAENG * and Masumi Ishikawa †

Abstract— **How to manage trade-off between exploitation and exploration in Particle Swarm Optimization (PSO) for efficiently solving various optimization problems is an important issue. In order to prevent premature convergence in PSO search, this paper proposes a new method, Particle Swarm Optimization with Diversive Curiosity (PSO/DC). A key idea of the proposed method is to introduce a mechanism of diversive curiosity into PSO for preventing premature convergence and for managing the exploration-exploitation trade-off. Diversive curiosity is represented by an internal indicator that detects marginal improvement of a swarm of particles for certain number of iterations, and forces them to continually explore an optimal solution to a given optimization problem. Applications of the proposed method to a 2-dimensional optimization problem well demonstrate its effectiveness. Our experimental results indicate that the performance (100%) by the proposed method is superior in terms of success ratio to that (60%) by the PSO model optimized by EPSO, and basically accord with the finding called "the zone of curiosity" in psychology.**

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

1 Introduction

Particle Swarm Optimization (PSO) is a new-type stochastic and population-based adaptive optimization algorithm proposed by Kennedy and Eberhart motivated by the social behavior in animals [4, 12]. In recent years, this technique has been widely applied to various disciplines in science and engineering such as applications to large-scale, highly nonlinear, and multimodal optimization problems [5, 8, 16, 19, 20, 21].

Similar to other search methods such as Reinforcement Learning (RL) [23, 24] and Genetic Algorithms (GAs) [7, 9, 15, 27], a trade-off between exploration and exploitation in PSO for efficiently solving various optimization problems is an important issue. An appropriate trade-off can activate swarm of particles in search to avoid premature convergence and to increase the accuracy and efficiency for finding an optimal solution to a given optimization problem [13, 31].

Considerable attention has been paid to this issue, and a number of algorithms for handling this have been proposed such as non-global best neighborhoods for increasing exploration and local search for increasing exploitation [2, 18, 22, 26]. Although these endeavors are effective in solving multimodal optimization problems, they suffer from heavy computational cost in managing the exploration-exploitation trade-off.

For obtaining still better search performance in PSO, we proposed Evolutionary Particle Swarm Optimization (EPSO) which used Real-coded Genetic Algorithm (RGA) to optimize PSO models with online computation [29, 32]. Since a temporally cumulative fitness function is used for effectually evaluating the performance of PSO, it is expected to suppress stochastic disturbance in dynamic evaluation, and EPSO greatly contributes to model selection in PSO without prior knowledge. Our experimental results for solving 2-dimensional multimodal optimization problem also demonstrated that the search performance of the PSO models optimized by EPSO is superior to the original PSO [29, 32].

Although the optimized PSO models have good search performance with moderate computational cost and accuracy, they still tend to be trapped in local minima (premature convergence) in solving multimodal optimization problems. This is a major reason that the efficiency of PSO does not improve in search.

To overcome this difficulty, we propose a new method, Particle Swarm Optimization with Diversive Curiosity (PSO/DC) [31]. Diversive curiosity here is a concept

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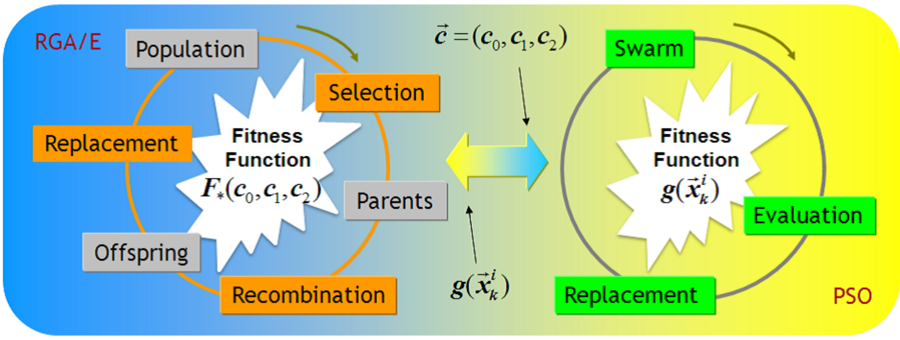

Figure 1: The flowchart of EPSO

in psychology: tendency of seeking stimulus/sensation in humans and animals. A key idea of the proposed method is to introduce a mechanism of diversive curiosity into PSO for preventing premature convergence and for managing the exploration-exploitation trade-off. Diversive curiosity is represented by an internal indicator that detects marginal improvement of a swarm of particles for certain number of iterations, and forces them to continually explore an optimal solution to a given optimization problem.

It is obvious that the concept of diversive curiosity introduced in PSO/DC is different from that in EPSO in managing the exploration-exploitation trade-off, which strengthens the swarm intelligence of PSO with a new strategy. The internal indicator in PSO/DC is simple with no extra computational cost. It has only two adjustable parameters, i.e., duration of judgment and a tolerance parameter: the former for memorizing the change of activity of a swarm of particles, and the latter for detecting premature convergence in search.

Similar to the internal indicator in PSO/DC, Adaptive Particle Swarm Optimization (APSO) was proposed [10]. In APSO, a fixed-$gBest$-value method was used for detecting dynamic changes of environment, which monitors the changes of the $gBest$ value and the second-best $gBest$ value for 20 iterations. Since the method checks whether the changes happen for the fixed duration or not, it is not only different from the formulation of the internal indicator mentioned in Section 3.3, but also it does not represent boredom. Common to APSO and PSO/DC is randomization of the entire swarm of particles for ensuring exploration.

Psychology asserts that diversive curiosity leads to exploration, but also creates anxiety [14]. Anxiety affects the efficiency of exploration. The relationship between the internal indicator and diversive curiosity, and its parameter selection were not discussed in [31] as a successful representation of engineering technique. It is, therefore, necessary to verify that the internal indicator in PSO/DC plays a role of the mechanism of diversive curiosity. It is also necessary to provide a method for parameter selection in the internal indicator. In addition to these, the effectiveness of PSO/DC in swarm intelligence should be demonstrated.

In our computer experiments, we use a 2-dimensional multimodal optimization problem. For practical efficacy of PSO/DC, we propose to estimate the appropriate range for the parameter values in the internal indicator to efficiently solve a given optimization problem. We also investigate the characteristics of PSO/DC, and the trade-off between exploration and exploitation in PSO/DC.

The rest of the paper is organized as follows. Section 2 briefly addresses an algorithm of EPSO, and two temporally cumulative fitness functions applied to evaluation of the performance of PSO. Section 3 describes a concept of curiosity, an internal indicator for diversive curiosity, and an algorithm of PSO/DC. Section 4 discusses the experimental results of computer experiments applied to a 2-dimensional multimodal optimization problem, analyzes the characteristics of PSO/DC, and compares the search performance with those by other methods such as the original PSO, EPSO and RGA/E. Finally, Section 5 gives conclusions.

2 Overview of EPSO

2.1 Basic EPSO

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

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

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

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

EPSO is an evolutionary algorithm with online computation, which provides a new paradigm for meta-optimization in model selection [29, 32]. Figure 1 illustrates the flowchart of EPSO.

The procedure of EPSO is composed of two parts. One is an outer loop in which Real-coded Genetic Algorithm with Elitism strategy (RGA/E) [28] is applied to solving real-valued optimization problems. While the PSO finds an optimal solution to a given optimization problem, RGA/E is used to optimize the values of parameters in the PSO. The other is an inner loop in which PSO runs. The PSO with the values of parameters created by RGA/E is expected to achieve higher fitness than the original PSO.

As the genetic operations of RGA/E, specifically, roulette wheel selection, BLX-α crossover [6], random mutation, and rank algorithm are used for optimization.

2.2 Fitness Functions

To effectually obtain PSO models with superior search performance, we use the following fitness functions [30, 31]. The first one is a temporally cumulative fitness function of the best particle,

$$F_1(c_0, c_1, c_2) = \sum_{k=1}^{K} g(\boldsymbol{x}_k^b)\big|_{c_0,c_1,c_2} \tag{2}$$

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

The second one is a temporally cumulative fitness function of the entire swarm, which is expressed by

$$F_2(c_0, c_1, c_2) = \sum_{k=1}^{K} \bar{g}_k\big|_{c_0,c_1,c_2} \tag{3}$$

where, $\bar{g}_k = \sum_{i=1}^{P} g(\boldsymbol{x}_k^i)/P$ is the average of fitness values over the entire swarm at time k.

It is obvious that the fitness functions, F_1 and F_2, stress distinctive character of same swarm of particles in search, respectively. For understanding the relationship between them, Figure 2 illustrates instantaneous fitness functions, $g(\boldsymbol{x}_k^b)$ and $\bar{g}_k$, and the corresponding cumulative fitness functions, F_1 and F_2. It is to be noted that F_1 and F_2 are approximately straight except near the origin. This suggests that both fitness functions, F_1 and F_2, are suitable for evaluating the performance of PSO.

Since the cumulative fitness functions, F_1 or F_2, are the sum of instantaneous fitness functions, $g(\boldsymbol{x}_k^b)$ or $\bar{g}_k$, over time, their variance is inversely proportional to the interval of summation. Therefore, two fitness functions can suppress stochastic perturbation in evaluation, and effectually select PSO models with superior search performance.

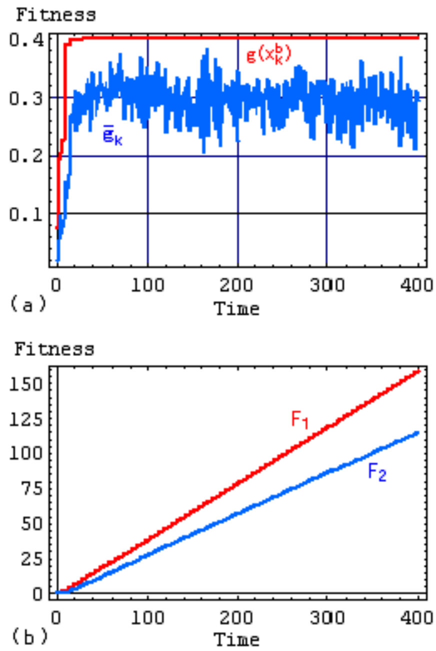

Figure 2: Comparison of two fitness functions. (a) $g(\vec{x}_k^b)$ and $\bar{g}_k$, (b) F_1 and F_2.

2.3 Convergence Speed

To evaluate the search ability of the entire swarm of particles for finding an optimal solution, we define the maximum time-step, k_{max}, as an indicator for convergence speed,

$$\forall k \geq k_{max}, \quad g(\boldsymbol{x}_k^b) - \bar{g}_k \leq \tau, \tag{4}$$

where τ is a positive tolerance parameter.

The smaller the maximum time-step, k_{max}, is, the faster the convergence speed of the swarm of particles is.

3 PSO/DC

3.1 Curiosity

Curiosity is a concept in psychology representing instinct for seeking of stimulus/sensation in humans and animals. Berlyne categorized it as *diversive curiosity* and *specific curiosity* [1]. Diversive curiosity signifies instinct to seek novelty, to take risks, and to search for adventure. Specific curiosity signifies instinct to investigate a specific object for its full understanding.

According to Berlyne's and his colleague Day's research [3], the diversive curiosity is aroused by external stimuli with complexity, novelty, uncertainty and conflict. The level of stimulation plays an essential role. If it is too low, it does not motivate a swarm of particles to explore; If it is too high, it will result in anxiety; If it is moderate, it motivates a swarm of particles to explore. Figure 3 illustrates an hypothesis of "zone of curiosity" in psychology.

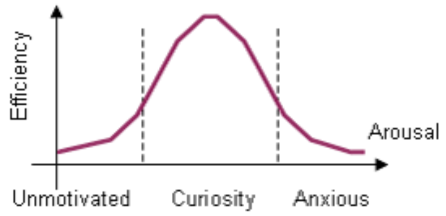

Figure 3: The zone of curiosity

Since the diversive curiosity makes a swarm of particles to continually seek novelty, and to escape boredom, the above hypothesis is applicable to PSO [25, 31]. How to realize the diversive behaviors of a swarm of particles by an engineering technique is a central issue [11, 17].

3.2 Internal Indicator

Loewenstein pointed out that "diversive curiosity occupies a critical position at the crossroad of cognition and motivation" [14]. Here, "cognition" is considered to be the act of precisely locating a solution (exploitation), and "motivation" is considered to be the intention of exploring the global solution (exploration). Exploitation is due to execution of specific diversive, and exploration is due to execution of diversive curiosity. Namely, a swarm of particles will carry out a conversion from specific curiosity to diversive curiosity at the position for the dissatisfaction to present situation such as premature convergence and search stagnation.

For representing the above conversion, the following internal indicator, y_k, is proposed for detecting premature convergence and escaping boredom.

$$y_k(L,\varepsilon) = max\Big(\varepsilon - \sum_{l=1}^{L} \frac{\big|g(\boldsymbol{x}_k^b) - g(\boldsymbol{x}_{k-l}^b)\big|}{L},\ 0\Big) \qquad (5)$$

where L is the duration of judgment, ε is a positive tolerance parameter for premature convergence.

Eq. (5) indicates that when the value of the internal indicator, y_k, is zero, the fitness value for $\boldsymbol{x}_k^b$ is still significantly changing, and when the value of the internal indicator, y_k, exceeds zero, the fitness value for $\boldsymbol{x}_k^b$ is not changing significantly. When y_k is positive, the internal indicator sends information to all particles to reinitialize their locations and velocities for finding other solutions in search space.

Since the internal indicator realizes the switching of policy from one situation (stagnation) to another (exploration) during PSO search, we may say that Eq. (5) plays a role of diversive curiosity for improving the search performance of PSO.

3.3 Procedure of PSO/DC

The internal indicator detects whether the swarm of particles continues to change or not and constantly makes them active to explore an optimal solution in search.

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 internal
    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 the gbest set;
End
```

It is to be noted that the optimized PSO models by EPSO described in Section 2 has superior search performance. Owing to the combination of EPSO and diversive curiosity, PSO/DC attains a good balance between exploration and exploitation for efficiently solving a given optimization problem.

4 Computer Experiments

4.1 Experimental Conditions

Table 1 gives the major parameters in EPSO.

Table 1: The major parameters used in EPSO.

Parameters	Value
The number of individuals, M	100
The number of generation, G	20
Roulette wheel selection	–
Probability of random mutation, p_m	1.0
Probability of BLX-2.0 crossover, p_c	1.0
The number of particle, P	10
The number of iterations, K	400
The maximum velocity, v_{max}	30

Table 2: Estimated parameter values in PSO and the frequency of the resulting models (top 20 models). PSO model in a-type: c_0 =0, c_1 =0, $c_2 \neq 0$; b-type: c_0 =0, $c_1 \neq$0, $c_2 \neq 0$; c-type: $c_0 \neq$0, c_1 =0, $c_2 \neq 0$; d-type: $c_0 \neq$0, $c_1 \neq$0, $c_2 \neq 0$.

Criterion	Optimized PSO	Parameter			Frequency
		c_0	c_1	c_2	
F_1	a-type	0	0	3.26±1.35	45%
	b-type	0	1.26±0.90	3.33±1.07	30%
	c-type	–	–	–	0%
	d-type	0.70±0.30	0.64±0.36	2.86±1.84	25%
F_2	a-type	0	0	2.00±0.52	40%
	b-type	0	0.37±0.39	2.00±0.07	30%
	c-type	0.15±0.00	0	1.34±0.25	20%
	d-type	0.16±0.01	0.75±0.32	1.19±1.16	10%

Computer experiments are carried out for investigating the characteristics and the search performance of PSO/DC for solving the given 2-dimensional multimodal optimization problem in Figure 4. The search space is limited to 60×60, and the fitness value of the optimal solution, $g(\boldsymbol{x}_g)$, is about 0.4.

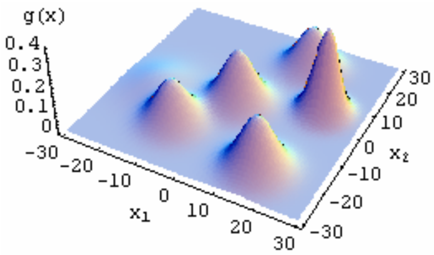

Figure 4: An optimization problem

4.2 Results of EPSO

All experiments were carried out with 20 trials. Table 2 shows the resulting parameter values of PSO models optimized by EPSO with two fitness functions [1] [2] . Comparing with these results, we observed that the EPSO generates 3 types or 4 types of PSO models which all can solve the given problem, regardless of the different frequency with top 20 models [3] .These results indicate that although the values of the inertial factor, c_0, and the individual confidence factor, c_1, could be zero, the value of the swarm confidence factor, c_2, is always non-zero in these models.

In general, the larger the average of fitness values is, the better the search performance of a model is. Under this rule, Figure 5 gives the mean and the standard deviation regarding the fitness values of the gbest for each model in Table 2. By comparing with the average of fitness values for each type of PSO model, it is obvious that the optimized PSO model in d-type has better search performance than other models.

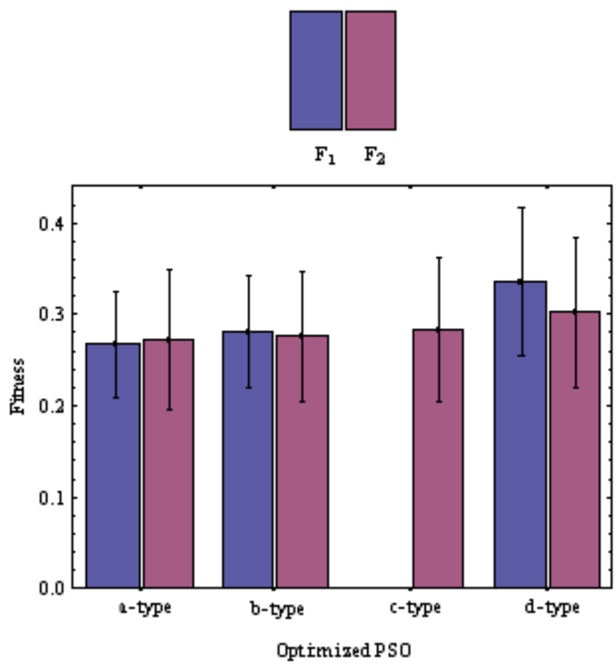

Figure 5: The mean and the standard deviation of fitness values for each type of PSO models.

Table 3 shows the performance index of the convergence speed, k_{max}, for representing the search activity of the entire swarm corresponding to the obtained each model. We observed that the maximum time-step created by the fitness function F_2 is smaller than that by the fitness function F_1. This means that the resulting PSO models generated by the fitness function F_2 converges faster than that by the fitness function F_1, and the exploration-exploitation trade-off created by the fitness function F_2 is inferior to that by the fitness function F_1. The ratio of the maximum time-step by the fitness function F_2 to

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

[2]It is to be noted that the values of parameters in PSO are estimated under the condition that parameters, c_0, c_1, and c_2, are non-negative.

[3]The reason why only top 20 models are included in Table 2 is that there are many PSO models with low fitness values due to an effort to keep the diversity of PSO models large.

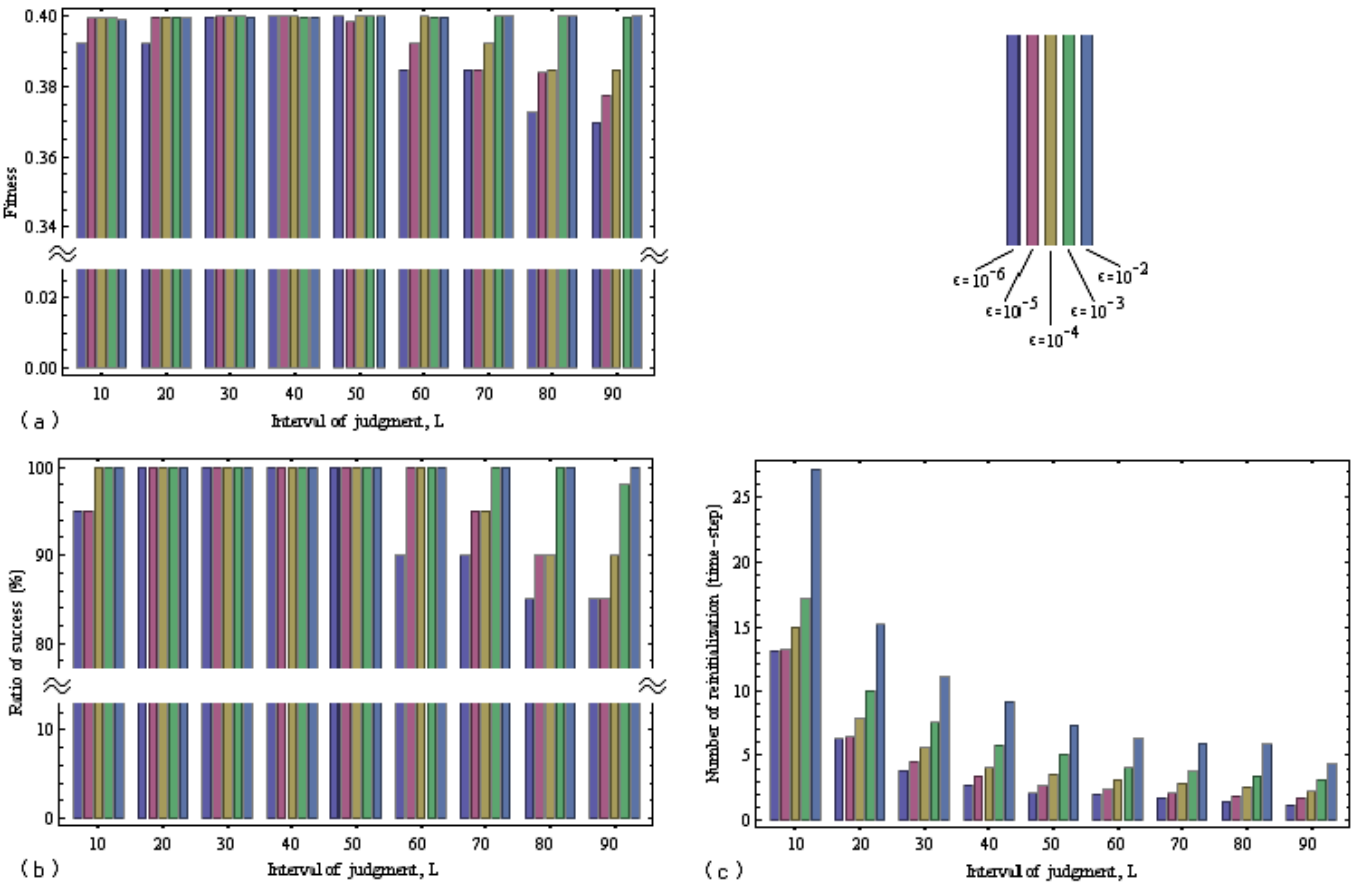

Figure 6: The performance indices of PSO/DC with two adjustable parameters. (a) The average of fitness values, (b) the number of reinitializations, (c) The ratio of success.

that by the fitness function F_1 is about 2.2% $\sim$ 29.0% in the experiments.

Table 3: The maximum time-step, k_{max}, for each model ($\tau = 0.03$).

Fitness Function	Optimized PSO			
	a-type	b-type	c-type	d-type
F_1	21.2±10.2	325.±69.2	–	81.5±30.3
F_2	6.15±1.46	7.30±2.84	5.65±0.58	6.05±0.94

The above experimental results accurately show the characteristics of two cumulative fitness functions, and directly give the hint to how to design PSO models.

4.3 Results of PSO/DC

According to the above results of EPSO, the optimized PSO model in d-type is adopted in PSO/DC for preventing premature convergence, managing the exploration-exploitation trade-off, and obtaining superior search performance to efficiently solve the given optimization problem.

For estimating appropriate range for the parameter values in the internal indicator, and investigating the search performance of PSO/DC, we change the values of parameters in the indicator, i.e., tolerance parameter, $\varepsilon = 10^{-6}$, 10^{-5}, 10^{-4}, 10^{-3}, 10^{-2} and duration of judgment, L=10, 20, 30, 40, 50, 60, 70, 80, 90, in the next experiments.

Figure 6 indicates the experimental results, i.e., the average of fitness values, the number of reinitialization, and the ratio of success [4] , of PSO/DC for each case. By comparing with the results, the characteristics of PSO/DC can be interpreted as follows.

1. From the results of the average of fitness values (Figure 6(a)) and the ratio of success (Figure 6(b)), these changes of the characteristics of PSO/DC with two adjustable parameters basically accord with the findings in psychology, i.e., curiosity may lead to exploration, but it also creates anxiety except for the tolerance parameter $\varepsilon = 10^{-3}$ or 10^{-2}. So to say, when L is longer, particles are hard to be excited (unmotivated) and when L is shorter, adversely they are easy to be excited (anxiety).

[4] Success refers to cases where particles reach the optimal solution. Success ratio is defined as the relative frequency of success.

2. From the results in Figure 6(c), with the increment of the duration of judgment, L, the number of reinitializations decrease nonlinearly.

3. By the situation of the fitness values of the best particle are kept to 0.4, the recommended range of the interval of judgment, L, is 30∼50.

4. By the situation of the ratio of success in each case can be kept to high level (98% ∼100%), the recommended range of the tolerance parameter, ε, is $10^{-3} \sim 10^{-2}$.

5. The average of fitness values or the ratio of success becomes small, when L or ε is outside of the recommended interval.

These results suggest that the effectiveness of the internal indicator representing the mechanism of diversive curiosity is certificated, even if the obtained experimental data are not so perfect when L is shorter and ε is bigger.

4.4 Feature of EPSO

For understanding the distinctive feature of PSO/DC in search, Figure 7 illustrates a variation of the instantaneous fitness value of the best particle in the limited search period.

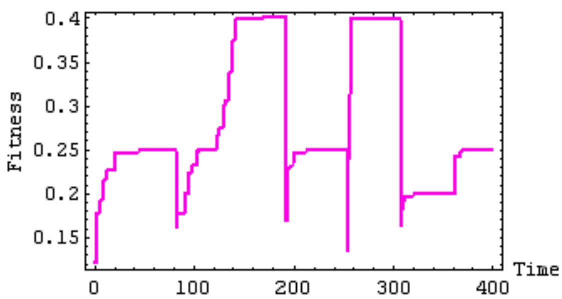

Figure 7: A variation of the fitness value of the best particle during search.

From the variation of the fitness value of the best particle in Figure 7, we observed that the number of reinitializations in the search period is four. Since the internal indicator effectively detects the activity of a swarm of particles, PSO/DC successfully avoided premature convergence four times for escaping boredom in this case. It indicates that the increment of reinitialization frequency can greatly improve the possibility for finding an optimal solution to the given optimization problem, and ensures the superior search performance of PSO/DC.

The increment of the reinitialization frequency also contributes to exploration. For the sake of visual effect, the whole plots of distribution density for the particles corresponding to EPSO and PSO/DC are shown in Figure 8.

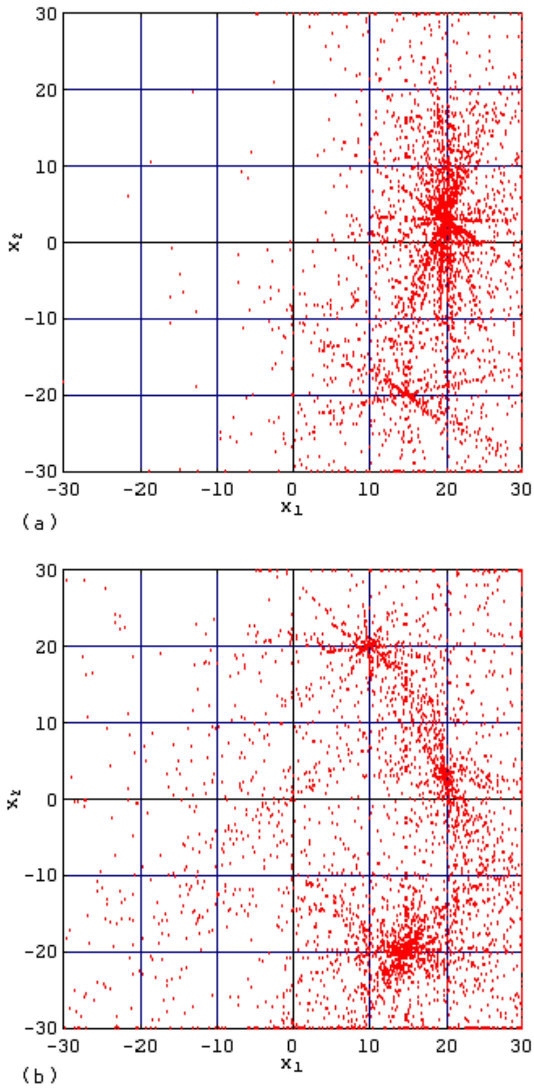

Figure 8: Distribution of the tracks of particles for each method. (a) EPSO, (b) PSO/DC.

We observed that the distribution region of the tracks of particles by PSO/DC in Figure 8(b) is bigger than that by EPSO in Figure 8(a), i.e., these particles are not only around few solutions, but also distributed over other space. This indicates that PSO/DC manages the exploration-exploitation trade-off well, and reflects the contribution of the internal indicator representing the mechanism of diversive curiosity for efficiently solving the given 2-dimensional multimodal optimization problem.

Figure 9 gives the resulting search performance for the original PSO, EPSO, PSO/DC$\sharp$ [5] , PSO/DC, RGA/E. By comparison with these results, we can confirm the following results.

- The search performance of each PSO method is su-

[5] It stands for the parameter values of the original PSO is used in PSO/DC.

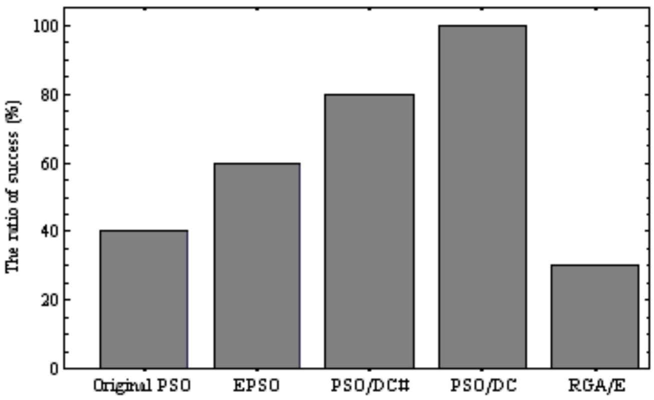

Figure 9: The ratio of success for each method with 20 trials.

perior to RGA/E.

- The search performance of PSO/DC (PSO/DC♯) is superior to that of EPSO (the original PSO).
- The search performance of EPSO is vastly improved by the mechanism of diversive curiosity.
- The search performance of PSO/DC♯ is superior to EPSO.

These results sufficiently indicate that the internal indicator plays an important role in efficiently solving the optimization problem, and the ratio of success finding the optimal solution, $\boldsymbol{x}_g$, corresponding to the given problem greatly improved from 60% to 100%.

5 Conclusions

We proposed Particle Swarm Optimization with Diversive Curiosity, PSO/DC. The key idea of the method is to introduce a mechanism of diversive curiosity into PSO. The mechanism is achieved by an internal indicator which detects premature convergence of a swarm of particles, and provides information to make them active to explore the global solution in search space. It can be interpreted as the mechanism of diversive curiosity.

Owing to the internal indicator representing the mechanism of diversity curiosity, PSO/DC can successfully prevent premature convergence, and manage the exploration-exploitation trade-off. Applications of PSO/DC to a 2-dimensional multimodal optimization problem well demonstrated its effectiveness. The ratio of success in finding the optimal solution to the given optimization problem is significantly improved, which reaches 100% with the estimated appropriate values of parameters in the internal indicator.

Empirically, PSO/DC is very effective in enhancing the search performance of PSO. Our experimental results basically accord with the findings called "the zone of curiosity" in psychology. Accordingly, the validity of the internal indicator introduced into PSO/DC was successfully verified. The basis of the PSO in swarm intelligence was further consolidated.

So far, only a 2-dimensional multimodal optimization problem was carried out for demonstrating the effectiveness of PSO/DC. It is left for further study to apply PSO/DC to high-dimensional benchmark problems, and to complex application problems in the real-world.

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