Proceedings of the International MultiConference of Engineers and Computer Scientists 2010 Vol I,
IMECS 2010, March 17 - 19, 2010, Hong Kong

Multiple Particle Swarm Optimizers with Diversive Curiosity

Hong Zhang, Member IAENG *

Abstract— **In this paper we propose a new method, called multiple particle swarm optimizers with diversive curiosity (MPSOα/DC), for improving the search performance of the convenient multiple particle swarm optimizers. It has three outstanding features: (1) Implementing plural particle swarms simultaneously to search; (2) Exploring the most suitable solution in a small limited space by a localized random search for correcting the solution found by each particle swarm; (3) Introducing diversive curiosity into the whole particle swarms to comprehensively deal with premature convergence and stagnation. To demonstrate the effectiveness of the proposed method, computer experiments on a suite of benchmark problems are carried out. We investigate the characteristics of the proposed method, and compare the search performance with other methods such as EPSO, OPSO, and RGA/E. The experimental results indicate that the search performance of MPSOα/DC is superior to EPSO, OPSO, and RGA/E for the given benchmark problems.**

Keywords: ***cooperative particle swarm optimization, hybrid computation, localized random search, exploitation and exploration, diversive and specific curiosity, swarm intelligence***

1 Introduction

As a new member of genetic and evolutionary computation (GEC) [1] , particle swarm optimization [9] has been rapidly developed since the last decade. Because of intuitive understandability, ease of implementation, and the ability to solve various optimization problems, this stochastic and population-based optimization method has been widely applied in various fields of science and technology [16, 17].

Many variants of the original particle swarm optimizer (PSO) such as PSO with inertia [18], canonical PSO [4], and fully informed particle swarm [10] were proposed for improving the convergence and search ability of PSO. The principal objective of these methods was mainly put in methodology, i.e. search strategy and information transfer in the interior of a particle swarm.

Whereas, in recent years, many studies and investigations on cooperative PSO in relation to symbiosis, group behavior, and sensational synergy are in the researcher's spotlight. Consequently, different forms of cooperative PSO, for example, cooperative PSO (CPSO S), hybrid PSO (CPSO H), and multi-population PSO (MCPSO) were published [1, 7] with deepening on group searching and search space resolution. In contrast to those methods that only operate a singular swarm, various attempts to the multi-swarm approach mainly focus on the rationality of information transfer and exchange within the plural particle swarms for significant enhancement of the search performance of PSO [3, 8, 14].

Due to great requests to search performance and swarm intelligence specially for social awareness and symbiosis in the real-world, utilizing the techniques of group searching and parallel processing in optimization has become one of extremely important approaches. Accordingly, the technique of cooperative PSO is taking on an essential mission in dealing with various optimization problems and actual applications as a current trend of the development of particle swarm optimization research.

This is the motivation to deepen the study for promoting new development of cooperative PSO research and the enhancement of swarm intelligence. In order to certainly realize the purpose, i.e. obtaining a practical cooperative PSO model with superior search performance, in this paper we propose a new method, called multiple particle swarm optimizers with diversive curiosity (MPSOα/DC [2]).

There are the following three strong points: (1) Decentralization in multi-swarm exploration with hybrid search (MPSOα) [3]; (2) Concentration in evaluation and state

*Hong Zhang is with the Department of Brain Science and Engineering, Graduate School of Life Science & Systems Engineering, Kyushu Institute of Technology, 2-4 Hibikino, Wakamatsu, Kitakyushu 808-0196, Japan (Tel/Fax: +81-93-695-6112; Email: zhang@brain.kyutech.ac.jp). The date of the manuscript submission is January 12, 2010.

[1]GEC usually refers to genetic algorithms (GA), genetic programming (GP), evolutionary programming (EP), and evolution strategies (ES).

[2]The sign, α, denotes that a localized random search is introduced into MPSO/DC, which explores the most suitable solution in a small limited space surrounding the solution found by PSO. When if the localized random search is not included or implemented in the procedure, the algorithm is called as MPSO/DC.

[3]The hybrid search, here, is composed of PSO search and the localized random search.

control with diversive curiosity (DC); (3) Their effective combination. These features are expected to effectively alleviate premature convergence and stagnation in optimization, and to improve the search performance of the convenient multiple particle swarm optimizers (i.e., cooperative PSO).

It is obvious that the essential search strategies and construction of MPSOα/DC are quite different from the existing methods such as parallel particle swarm optimization proposed by Chang et al. [3], which only implements plural PSO simultaneously and hybrid genetic algorithm and particle swarm optimization proposed by Juang [8], which implements GA and PSO by the mixed operation to a singular swarm. Accordingly, the integrated search strategies and their effective combination are considered as the originality of MPSOα/DC. The proposed method is suitable to complex search environments and to efficient solving of various optimization problems by comprehensive management of the trade-off between exploitation and exploration [5, 20].

The rest of the paper is organized as follows. Section 2 describes basic architectures including algorithms of PSO, EPSO, LRS, and internal indicator. Section 3 introduces an algorithm of MPSOα/DC and its characteristics. Section 4 analyzes and discusses the results of computer experiments applied to a suite of five-dimensional (5D) benchmark problems. Finally Section 5 gives the conclusions.

2 Basic Architecture

This section describes the mechanism of PSO, a localized random search, and internal indicator, respectively.

2.1 Particle Swarm Optimizer

Let the search space be N-dimensional, $\mathbf{\Omega} \in \Re^N$, the number of particles in a swarm be P, the position of the ith particle be $\vec{x}^i = (x_1^i, x_2^i, \cdots, x_N^i)^T$, and its velocity be $\vec{v}^i = (v_1^i, v_2^i, \cdots, v_N^i)^T$. In the beginning of PSO search, the particle's position and velocity are generated in random, then they are updated by

$$\begin{cases} \vec{x}^i_{k+1} = \vec{x}^i_k + \vec{v}^i_{k+1} \\ \vec{v}^i_{k+1} = c_0\vec{v}^i_k + c_1\vec{r}_1 \otimes (\vec{p}^i_k - \vec{x}^i_k) + c_2\vec{r}_2 \otimes (\vec{q}_k - \vec{x}^i_k) \end{cases} \quad (1)$$

where c_0 is an inertial coefficient, c_1 is a coefficient for individual confidence, c_2 is a coefficient for swarm confidence. $\vec{r}_1, \vec{r}_2 \in \Re^N$ are two random vectors in which each element is uniformly distributed over $[0, 1]$, and $\otimes$ is an element-by-element multiplication operator. $\vec{p}^i_k (= arg \max_{j=1,\cdots,k} \{g(\vec{x}^i_j)\}$, where $g(\cdot)$ is the fitness value of the ith particle at time-step k.) is the local best position of the ith particle up to now, and $\vec{q}_k (= arg \max_{i=1,2,\cdots} \{g(\vec{p}^i_k)\})$ is the global best position among the whole swarm up to now. In the original PSO, the values of parameter, $c_0 = 1.0$ and $c_1 = c_2 = 2.0$, are set [9].

2.2 Localized Random Search

As common sense in optimization, random search methods are the simplest ones of stochastic optimization, and are effective in many problems [19]. For obtaining higher search performance, in this paper we propose to use LRS which explores the most suitable solution from a limited space surrounding the solution found by PSO. The procedure of LRS is implemented as follows.

step 1: Let $\vec{q}^s_k$ to be a solution found by the sth particle swarm at time-step k, and set $\vec{q}^s_{now} = \vec{q}^s_k$. Give the terminating condition, J (the total number of random data), and set $j = 1$.

step 2: Generate a random data, $\vec{d}_j \sim N(0, \sigma_N^2)$ (where σ_N is a small positive value given by user, which determines the small limited space). Check whether $\vec{q}^s_k + \vec{d}_j \in \mathbf{\Omega}$ is satisfied or not. If $\vec{q}^s_k + \vec{d}_j \notin \mathbf{\Omega}$ then adjust $\vec{d}_j$ for moving $\vec{q}^s_k + \vec{d}_j$ to the nearest valid point within $\mathbf{\Omega}$. Set $\vec{q}_{new} = \vec{q}^s_k + \vec{d}_j$.

step 3: If $g(\vec{q}_{new}) > g(\vec{q}^s_{now})$ then set $\vec{q}^s_{now} = \vec{q}_{new}$.

step 4: Set $j = j + 1$. If $j \le J$ then go to **step 2**.

step 5: Set $\vec{q}^s_k = \vec{q}^s_{now}$ to correct the solution found by the sth particle swarm. Stop the search.

Because the search is localized to a small limited space, the execution of LRS is expected to rapidly locate the most suitable solution with heuristic.

2.3 Internal Indicator

Curiosity, as a general concept in psychology, is an emotion related to natural inquisitive behavior for humans and animals, and its importance and effect in motivating search cannot be ignored [6, 15]. For clarifying the potential causes, Berlyne categorized it into two types: diversive curiosity and specific curiosity [2]. In the matter of the mechanism of the former, Loewenstein insisted that "diversive curiosity occupies a critical position at the crossroad of cognition and motivation" in [11].

Based on the assumption of "cognition" is the act of exploitation, and "motivation" is the intention to exploration, Zhang et al. proposed the following model of internal indicator to specification [24, 25].

$$y_k(L, \varepsilon) = max\Big(\varepsilon - \sum_{l=1}^{L} \frac{\big|g(\vec{q}^b_k) - g(\vec{q}^b_{k-l})\big|}{L},\ 0\Big) \quad (2)$$

where $\vec{q}^b_k (= arg \max_{s=1,\cdots,S} \{g(\vec{q}^s_k)\}$, where S is the total number of plural particle swarms) denotes the best solution found by the whole particle swarms at time-step k. L is duration of judgment (endurance), and ε is the positive tolerance coefficient (sensitivity).

3 Proposed MPSOα/DC

Figure 1 illustrates the flowchart of the proposed method, MPSOα/DC. The most difference to the existing method PSO/DC [24, 25] in construction is that plural particle swarms are implemented simultaneously to explore, and LRS is used to correct the solution found by each particle swarm, respectively. Here, the hybrid search only consists of both PSO and LRS (i.e. memetic algorithm [13]). Consequently, the best solution, $\vec{q}_k^b$, found by the multi-swarm is determined by maximum comparison, and it is kept to judge the search condition, and to control the behavior of multi-swarm search for a specified time-step.

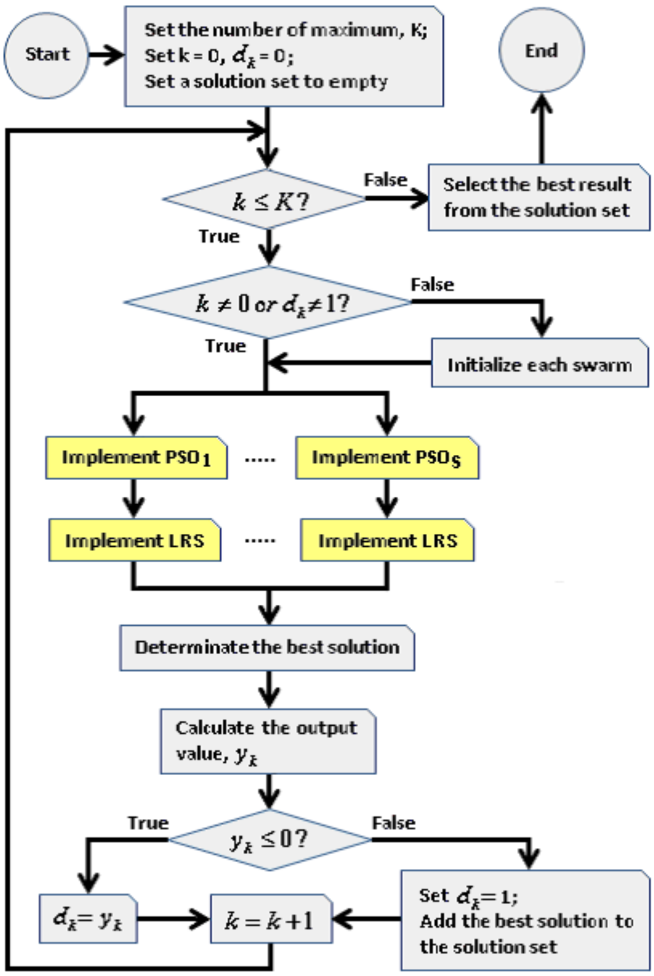

Figure 1: Flowchart of the proposed MPSOα/DC

The mission of the internal indicator is to monitor whether the status of the best solution $\vec{q}_k^b$ continues to change or not. While the value of the output y_k is zero, i.e. the value of cumulative criterion, $\sum_{l=1}^{L} |g(\vec{q}_k^b) - g(\vec{q}_{k-l}^b))|$, is still bigger than the value of sensitivity ε, this means that the multi-swarm is exploring the surroundings of the solution $\vec{q}_k^b$ for "cognition". If once the value of the output y_k become positive, this means that the multi-swarm has lost interest, i.e. feeling boredom, in the solution $\vec{q}_k^b$ for "motivation". Namely, the multi-swarm identifies that the phenomena of premature convergence or stagnation occur at present, and spontaneously sends a control signal, $d_k = 1$, to make each particle swarm active by reinitialization for exploring other unknown solutions in the search space, Ω, as a resort of escaping boredom.

In addition, the PSO models optimized by evolutionary particle swarm optimization (EPSO) [22, 23] are used in MPSOα/DC for ensuring higher search performance. Therefore, EPSO is carried out as a preliminary step for obtaining the optimized PSO models to the given various optimization problems before the execution of MPSOα/DC.

4 Computer Experiments

To facilitate comparison and analysis of the performance of the proposed method, MPSOα/DC, we use the following suite of multidimensional benchmark problems [26].

Sphere function:

$$f_{Sp}(\vec{x}) = \sum_{d=1}^{N} x_d^2$$

Griewank function:

$$f_{Gr}(\vec{x}) = \frac{1}{4000}\sum_{d=1}^{N} x_d^2 - \prod_{d=1}^{N} cos\Big(\frac{x_d}{\sqrt{d}}\Big) + 1$$

Rastrigin function:

$$f_{Ra}(\vec{x}) = \sum_{d=1}^{N} \Big(x_d^2 - 10\,cos\,(2\pi x_d) + 10\Big)$$

Rosenbrock function:

$$f_{Ro}(\vec{x}) = \sum_{d=1}^{N-1} \Big[\Big(100(x_{d+1} - x_d^2)\Big)^2 + (x_d - 1)^2\Big]$$

For finding an optimal solution corresponding to each benchmark problem, the following fitness function regarding the search space, $\mathbf{\Omega} \in (-5.12, 5.12)^N$, is defined by

$$g_\omega(\vec{x}) = \frac{1}{f_\omega(\vec{x}) + 1}, \tag{3}$$

where the subscript, ω, stands for one of the followings: *Sp* (*Sphere*), *Gr* (*Griewank*), *Ra* (*Rastringin*), and *Ro* (*Rosenbrock*), respectively.

Table 1 gives the major parameters used in EPSO and MPSOα/DC. In the beginning of MPSOα/DC search, positions of all particles in the used multi-swarm are set randomly, and their velocities are set to zero.

Table 2 indicates the resulting values of parameters in

ISBN: 978-988-17012-8-2
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

Table 1: The major parameters used in EPSO and MPSOα/DC

Parameters	Value
the number of individuals, M	10
the number of generation, G	20
probability of BLX-2.0 crossover, p_c	0.5
probability of random mutation, p_m	0.5
the number of particles, P	10
the number of iterations, K	400
the maximum velocity, v_{max}	5.12
the number of particle swarms, S	3
the range of LRS, σ_N^2	0.05
the number of LRS runs, J	10

PSO models corresponding to each 5D benchmark problem with 20 trials [4], which are selected by comparison of search performance.

Table 2: The resulting values of parameters in PSO models for each 5D benchmark problem.

Problem	Parameters in PSO		
	c_0	c_1	c_2
Sphere	0.677±0.23	1.129±0.09	0.937±0.65
Griewank	0.510±0.26	2.086±0.42	1.025±0.61
Rastrigin	1.345±0.54	10.28±3.52	24.92±21.8
Rosenbrock	0.902±0.06	1.309±0.56	0.761±0.16

From Table 2, we observed that the average of the parameter values are quite different from that of the original PSO, and the average of the parameter values, c_0, of the PSO models optimized by EPSO are less than 1 except for the *Rastrigin* problem. This suggests that the active behavior of particles is convergence in exploring an optimal solution corresponding to each given problem. In contrast to this, the average of the parameter values in PSO model, c_0, drastically exceeds 1 that means that the exploration needs to have more randomization without restriction for the *Rastrigin* problem.

These experimental results emphasize the importance of implementing EPSO in obtaining the optimized PSO models without prior knowledge. These PSO models in Table 2 as PSO* are adopted in MPSOα/DC for ensuring the convergence and search accuracy.

For investigating the characteristics of MPSO*α/DC, the experiments were carried out by tuning the parameters, L and ε, of the internal indicator. Figure 2 gives the resulting search performance of MPSO*α/DC, which include the average of fitness values and the average of reinitialization frequencies for each given problem. From Figure

[4]Computing environment: Intel(R) Xeon(TM); CPU 3.40GHz; Memory 2.00GB RAM; Computing tool: Mathematica 5.2; Computing time: about 13 min.

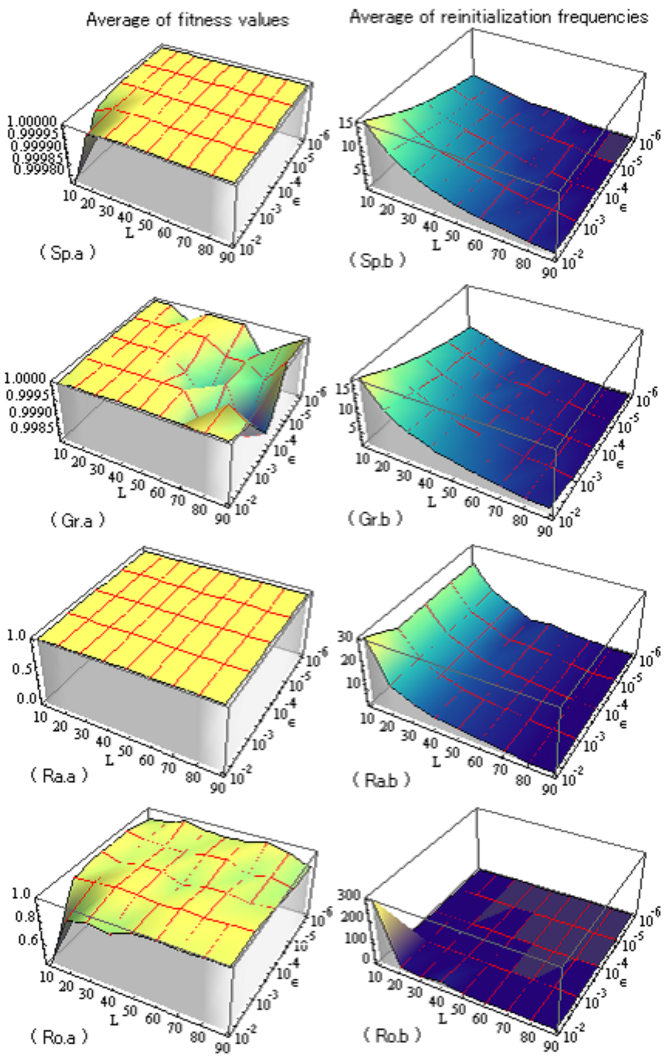

Figure 2: Distribution of the obtained results with tuning the parameter values in the indicator for each problem. (b) Average of fitness values, (c) Average of reinitialization frequencies.

2, the following characteristics of MPSO*α/DC are observed.

- The averages of reinitialization frequencies seem to monotonously increase with increment of the tolerance parameter, ε, and decrement of the duration of judgment, L, for every problem. Whereas, the changes of the average of fitness values are non-monotounous.
- The average of fitness values does not change at all with tuning the parameters, L and ε, for the *Rastrigin* problem.
- For obtaining the superior search performance of MPSO*α/DC, the recommended range of the parameters, $L^*_{Sp} \in (30 \sim 90)$ and $\varepsilon^*_{Sp} \in (10^{-6} \sim 10^{-4})$ for the *Sphere* problem; $L^*_{Gr} \in (20 \sim 50)$ and $\varepsilon^*_{Gr} \in (10^{-5} \sim 10^{-3})$ for the *Griewank* problem; $L^*_{Ra} \in (10 \sim 90)$ and $\varepsilon^*_{Ra} \in (10^{-6} \sim 10^{-2})$

ISBN: 978-988-17012-8-2
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

Table 3: The mean and standard deviation of fitness values in each method for each 5D benchmark problem with 20 trials (The values in bold signify the best result for each problem).

Problem	MPSO*α/DC	EPSO	OPSO	RGA/E
Sphere	**1.0000**±0.000	**1.0000**±0.000	**1.0000**±0.000	0.9980±0.0016
Griewank	**1.0000**±0.000	0.9876±0.0104	0.9448±0.0439	0.7966±0.1175
Rastrigin	**1.0000**±0.000	**1.0000**±0.000	0.2652±0.1185	0.9616±0.0239
Rosenblock	**0.9893**±0.012	0.4694±0.2806	0.3926±0.1976	0.3723±0.1364

for the *Rastrigin* problem; $L^*_{Ro} \in (40 \sim 80)$ and $\varepsilon^*_{Ro} \in (10^{-4} \sim 10^{-3})$ for the *Rosenbrock* problem are available, respectively.

As to the *Rastrigin* problem, the resulting best fitness value and the average of fitness values are mostly unchanged with tuning the parameters, L and ε. This phenomenon indicates that the PSO model optimized by EPSO will be sufficient to handle the multimodal optimization problem well.

On the other hand, due to stochastic factor in PSO search and complexity of the given benchmark problems, some irregular change of the experimental results can be discovered in Figure 2 (Gr.a) and (Ro.a). Moreover, because of the effect of the adopted hybrid search, the fundamental finding, "the zone of curiosity," in psychology [6] is not distinguished except for the *Rosenbrock* problem. The top curve of "the average of fitness values" seems to be a plane without the change of the parameters, L and ε. This suggests that the proposed method, MPSO*α/DC, has a good adaptability.

We observed that the average of reinitialization frequencies is over 300 at the case of the parameters, L=10 and $\varepsilon = 10^{-2}$, for the *Rosenbrock* problem in Figure 2 (Ro.b). The average of fitness values is the lowest than that by other cases. This means that the active exploring of the whole particle swarms seems to have entered "the zone of anxiety," which is the reason leading the search performance of MPSO*α/DC to be lower. In the opposite sense, this result also indicates that the effect of diversive curiosity is conspicuous to relatively complex problems, because the used method has powerful ability in search.

For further illuminating the effectiveness of the proposed method, here we compare the search performance with other methods such as EPSO, OPSO (optimized particle swarm optimization) [12], and RGA/E (real-coded genetic algorithm with elitism strategy) [21].

Table 3 gives the experimental results of implementing these methods with 20 trials. It is well shown that the search performance of MPSO*α/DC is better than that by EPSO, OPSO, and RGA/E by comparison with the average of fitness values. The results sufficiently reflect that the merging of both multiple hybrid search and the mechanism of diversive curiosity takes the active role in handling various optimization problems. In particular, we observed that a big increase, i.e. the average of fitness values grows from 0.4694 to 0.9893, in search performance is achieved well for the *Rosenbrock* problem.

5 Conclusions

A new method of multiple particle swarm optimizers with diversive curiosity, MPSOα/DC, has been proposed in this paper. Owing to the essential concept of decentralization in search and concentration in evaluation and state judgment, the combination of the adopted hybrid search and the execution of diversive curiosity, theoretically, has good capability, which greatly improves the search accuracy to the best solution and alleviates premature convergence and stagnation by comprehensive management of the trade-off between exploitation and exploration in multiple particle swarms run.

Applications of MPSOα/DC to a suite of 5D benchmark problems well demonstrated its effectiveness. The experimental results verified that unifying the both characteristics of multiple hybrid search and LRS is successful and effective in convergence and adaptability. By comparing the search performance of EPSO, OPSO, and RGA/E, it is confirmed that the proposed method has an enormous latent capability in handling different benchmark problems.

The experimental results of MPSOα/DC are verifiable, and basically accord with the fundamental finding, "the zone of curiosity," in psychology. Accordingly, the basis of the development study of cooperative PSO research in swarm intelligence is expanded and consolidated.

It is left for further study to apply MPSOα/DC to complex problems in the real-world and dynamic environments, and to expect that the fruitful results can be obtained in its applications.

References

[1] Bergh, F. van den, Engelbrecht, A.P., "A cooperative approach to particle swarm optimization," *IEEE Transactions on Evolutionary Computation*, Vol.8, Issue 3, pp.225-239, 2004.

[2] Berlyne, D., *Conflict, arousal, and curiosity.* McGraw-Hill Book Co., New York, USA, 1960.

[3] Chang, J.F., Chu, S.C., Roddick, J.F., Pan, J.S., "A parallel particle swarm optimization algorithm with communication strategies," *Journal of information science and engineering*, No.21, pp.809-818, 2005.

[4] Clerc, M., Kennedy, J., "The particle swarm-explosion, stability, and convergence in a multidimensional complex space," *IEEE Transactions on Evolutionary Computation*, Vol.6, No.1, pp.58-73, 2000.

[5] Cohen, J.D., McClure, S.M., Yu, A.J., "Should I stay or should I go? How the human brain manages the trade-off between exploitation and exploration," *Philosophical Transactions of The Royal Society*, Part B, No.362, pp.933-942, 2007.

[6] Day, H., "Curiosity and the Interested Explorer," *Performance and Instruction*, Vol.21, No.4, pp.19-22, 1982.

[7] El-Abd, M., Kamel, M.S., "A Taxonomy of Cooperative Particle Swarm Optimizers," *International Journal of Computational Intelligence Research*, ISSN 0973-1873, Vol.4, No.2, pp.137-144, 2008.

[8] Juang, C.-F., "A Hybrid of Genetic Algorithm and Particle Swarm Optimization for Recurrent Network Design," *IEEE Transactions on Systems, Man and Cybernetics*, Part B, Vol.34, No.2, pp.997-1006, 2004.

[9] Kennedy, J., Eberhart, R.C., "Particle swarm optimization," *Proceedings of the 1995 IEEE International Conference on Neural Networks*, pp.1942-1948, Piscataway, New Jersey, USA, 4/95.

[10] Kennedy, J., Mendes, R., "Population structure and particle swarm performance," *Proceedings of the IEEE Congress on Evolutionary Computation* (CEC2002), Honolulu, Hawaii, USA, pp.1671-1676, 5/02.

[11] Loewenstein, G., "The Psychology of Curiosity: A Review and Reinterpretation," *Psychological Bulletin*, Vol.116, No.1, pp.75-98, 1994.

[12] Meissner, M., Schmuker, M., Schneider, G., "Optimized Particle Swarm Optimization (OPSO) and its application to artificial neural network training," *BMC Bioinformatics*, Vol.7, No.125, 2006.

[13] Moscato, P., "On Evolution, Search Optimization, Genetic Algorithms and Martial Arts: Towards Memetic Algorithms," *Technical Report Caltech Concurrent Computation Program*, Report 826, California Institute of Technology, Pasadena, CA 91125, 1989.

[14] Niu, B., Zhu, Y., He, X., "Multi-population Cooperation Particle Swarm Optimization," *LNCS*, No.3630, pp.874-883, Springer Heidelberg, DOI 10.1007/11553090_88, 2005.

[15] Opdal, P.M., "Curiosity, Wonder and Education seen as Perspective Development," *Studies in Philosophy and Education*, Vol.20, No.4, pp.331-344, Springer Netherlands, DOI 10.1023/A:1011851211125, 2001.

[16] Poli, R., Kennedy, J., Blackwell, T., "Particle swarm optimization — An overview," *Swarm Intell*, Vol.1, pp.33-57, DOI 10.1007/s11721-007-0002-0, 2007.

[17] Reyes-Sierra, M., Coello, C.A.C., "Multi-Objective Particle Swarm Optimizers: A Survey of the State-of-the-Art," *International Journal of Computational Intelligence Research*, Vol.2, No.3, pp.287-308, 2006.

[18] Shi, Y., Eberhart, R.C., "A modified particle swarm optimiser," Proceedings of the IEEE International Conference on Evolutionary Computation, pp.69-73, Piscataway NJ, IEEE Press, 1998.

[19] Solis, F.J., Wets, R.J-B., "Minimization by Random Search Techniques," *Mathematics of Operations Research*, Vol.6, No.1, pp.19-30, 1981.

[20] Spall, J.C., "Stochastic Optimization," In: J. Gentle et al. (eds.), *Handbook of Computational Statistics*, Springer Heidelberg, pp.169-197, 2004.

[21] Zhang, H., Ishikawa, M., "A Hybrid Real-Coded Genetic Algorithm with Local Search," *Proceedings of the 12th International Conference on Neural Information Processing* (ICONIP2005), Taipei, Taiwan, ROC, pp.732-737, 10/05.

[22] Zhang, H., Ishikawa, M., "Evolutionary Particle Swarm Optimization (EPSO) – Estimation of Optimal PSO Parameters by GA," Proceedings of the IAENG International MultiConference of Engineers and Computer Scientists 2007 (IMECS2007), Hong Kong, China, Vol.1, pp.13-18, 3/07.

[23] Zhang, H., Ishikawa, M., "Evolutionary Particle Swarm Optimization – Metaoptimization Method with GA for Estimating Optimal PSO Methods," In: O. Castillo, et al. (eds.), *Trends in Intelligent Systems and Computer Engineering*, Lecture Notes in Electrical Engineering, Vol.6, pp.75-90, Springer Heidelberg, 2008.

[24] Zhang, H., Ishikawa, M., "Particle Swarm Optimization with Diversive Curiosity – An Endeavor to Enhance Swarm Intelligence," *IAENG International Journal of Computer Science*, Vol.35, Issue 3, pp.275-284, 2008.

[25] Zhang, H., Ishikawa, M., "Characterization of particle swarm optimization with diversive curiosity," *Journal of Neural Computing & Applications*, pp.409-415, Springer London, DOI 10.1007/s00521-009-0252-4, 2009.

[26] http//:www.ntu.edu.sg/home/epnsugan/index_files/CEC-05/Tech-Report-May-30-05.pdf

ISBN: 978-988-17012-8-2
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)