Scientific Research and Essays Vol. 6(22), pp. 4848-4855, 7 October, 2011
Available online at http://www.academicjournals.org/SRE
DOI: 10.5897/SRE11.1291
ISSN 1992-2248 ©2011 Academic Journals

Full Length Research Paper

Social emotional optimization algorithm with group decision

Zhihua Cui[1,2,3]* Xingjuan Cai[1] and Zhongzhi Shi[3]

[1]Complex System and Computational Intelligence Laboratory, Taiyuan University of Science and Technology, Shanxi, 030024, China.
[2]State Key Laboratory of Novel, Software Technology, Nanjing University, 210093, China.
3The Key Laboratory of Intelligent Information Processing, Institute of Computing Technology, Chinese Academy of Sciences, Beijing, China, 100190.

Accepted 17 August, 2011

Social emotional optimization algorithm (SEOA) is a new swarm intelligent technique by simulating human social behaviors. In SEOA, each individual represents a virtual person and pursues high society status by selecting the behaviors according to the corresponding emotional index in each iteration. Therefore, how to simulate the personal decision mechanism plays an important role for the algorithm performance. In this paper, group decision mechanism is introduced into methodology of SEOA to simulate the human decision phenomenon. In this new variant, each person will make his decision not only with his experiences, but also with other individuals' experiences. To test the performance, four famous unconstraint numerical benchmarks are selected, and simulation results show it is effective when compared with other three swarm intelligent algorithms especially for high-dimensional cases.

Key words: Social emotional optimization algorithm, group decision mechanism, emotional index.

INTRODUCTION

Swarm intelligence (SI) is a recent research topic which mimics the animal social behaviors. Up till now, many new SI algorithms have been proposed, such as group search optimizer (He et al., 2006), artificial physics optimization (Xie et al., 2010) and firefly algorithm (Yang, 2010). The most famous two are ant colony optimizer and particle swarm optimization. Ant colony optimizer (ACO) (Laalaoui and Drias, 2010) and particle swarm optimizer (Abraham et al., 2010; Yuan and Chen, 2010; Lu et al., 2010; Upendar et al., 2010) simulate ant seeking and fish schooling behaviors, respectively. Compared with them, SEOA has a remarkable superior performance in terms of accuracy and convergence speed. As a new population-based stochastic optimization algorithm, SEOA was proposed by Zhihua et al. (2010) (Cui and Cai, 2010; Chen et al., 2010; Cui et al., 2010, Wei et al., 2010; Xu et al., 2010). In SEOA methodology, each individual represents one person, while all points in the problem space constructs the status society. In this virtual world, all individuals aim to seek the higher social status. Therefore, they will communicate through cooperation and competition to increase personal status, while the one with highest score will win and output as the final solution. In the standard version of SEOA, only one individual with highest social status provides some advices to help other individuals' decision. This phenomenon confuse with natural human society voting. By the way, although his social status is the highest, his advice may be right in some cases, while others may provide wrong comments. To avoid this shortcoming, in this paper, a group decision mechanism is introduced to improve the performance of SEOA.

*Corresponding author. E-mail: cuizhihua@gmail.com.

Abbreviations: SEOA, Social emotional optimization algorithm; **SI,** swarm intelligence; **ACO,** ant colony optimizer; **SPSO,** standard particle swarm optimization; **MPSO-TVAC,** modified particle swarm optimizxation with time-varying accelerator coefficients.

MATERIALS AND METHODS

Social emotional optimization algorithm

Without loss of generality, we consider the following unconstrained problem:

$$\min f(X) \quad X \in D \in R^n$$

In human society, people do their work hardly to increase their social status. To obtain this object, people will try their bests to find the path so that more social wealth's can be rewarded. Inspired by this phenomenon, Cui et al. (2010) proposed a new population-based swarm methodology, social emotional optimization algorithm, in which each individual simulates a virtual person whose decision is guided by his emotion. In social emotional optimization algorithm methodology, each individual represents a virtual person, in each generation, he will select his behavior according to the corresponding emotion index. After the behavior is done, a status value is feedback from the society to confirm whether this behavior is right or not. If this choice is right, the emotion index of himself will increase, and vice versa. In the first step, all individuals' emotion indexes are set to 1, with this value, they will choice the following behavior:

$$\overline{x_j}(1) = \overline{x_j}(0) \oplus manner_1 \tag{1}$$

Where $\overline{x_j}(1)$ represents the social position of j's individual in the initialization period, the corresponding fitness value is denoted as the society status. Symbol $\oplus$ means the operation, in this paper, we only take it as addition operation +. Since the emotion index of j is 1, the movement phase $manner_1$ is defined by:

$$Manner_1 = -k_1.rand_1.\sum_{\varepsilon=1}^{L}(\overline{x_\varepsilon}(0) - \overline{x_j}(0)) \tag{2}$$

Where k_1 is a parameter used to control the size, $rand_1$ is one random number sampled with uniform distribution from interval (0 and 1). The worst L individuals are selected to provide a reminder for individual j to avoid the wrong behaviors. In t generation, if individual j does not obtain one better society status value than previous value, the j's emotion index is decreased as follows:

$$BI_j(t+1) = BI_j(t) - \Delta \tag{3}$$

Where Δ is a predefined value, and set to 0.05, this value is coming from experimental tests. If individual j is rewarded a new status value which is the best one among all previous iterations, the emotion index is reset to 1.0:

$$BI_j(t+1) = 1.0 \tag{4}$$

Remark: According to Equation (3), $BI_j(t+1)$ is no less than 0.0, in other words, if $BI_j(t+1) < 0.0$, then $BI_j(t+1) = 0.0$. In order to simulate the behavior of human, three kinds of manners are designed, and the next behavior is changed according to the following three cases:

If $BI_j(t+1) < TH_1$

$$\overline{x_j}(t+1) = \overline{x_j}(t) + manner_2 \tag{5}$$

If $TH_1 < BI_j(t+1) < TH_2$

$$\overline{x_j}(t+1) = \overline{x_j}(t) + manner_3 \tag{6}$$

Otherwise

$$\overline{x_j}(t+1) = \overline{x_j}(t) + manner_4 \tag{7}$$

Two parameters TH_1 and TH_2 are two thresholds aiming to restrict the different behavior manner. For Case1, because the emotion index is too small, individual j prefers to simulate others' successful experiences. Therefore, the update equation is:

$$Manner_2 = k_2.rand_2.(\overline{Status_{best}}(t) - \overline{x_j}(t)) \tag{8}$$

Where $\overline{Status_{best}}(t)$ represents the best society status position obtained from all people previously. In other words, it is:

$$\overline{Status_{best}}(t) = \arg\min\{f(\overline{x_\varepsilon}(h) \mid 1 \le h \le t)\} \tag{9}$$

With the similar method, Manner_3 is defined:

$$Manner_3 = k_3.rand_3.(\overline{X_{jbest}}(t) - \overline{x_j}(t)) + k_2.rand_2.$$
$$(\overline{Status_{best}}(t) - \overline{x_j}(t)) - k_1.rand_1.\sum_{\varepsilon=1}^{L}(\overline{x_\varepsilon}(0) - \overline{x_j}(0)) \tag{10}$$

While $\overline{X_{jbest}}(t)$ denotes the best status value obtained by individual j previously, and is defined by

$$\overline{X_{jbest}}(t) == \arg\min\{f(\overline{x_j}(h) \mid 1 \le h \le t)\} \tag{11}$$

For Manner_4, we have

$$Manner_4 = k_3.rand_3.(\overline{X_{jbest}}(t) - \overline{x_j}(t)) - k_1.rand_1.\sum_{\varepsilon=1}^{L}(\overline{x_\varepsilon}(0) - \overline{x_j}(0)) \tag{12}$$

To enhance the global capability, a mutation strategy, similarly with evolutionary computation, is introduced to enhance the ability escaping from the local optima, more details of this mutation operator is the same as Cai et al. (2008), please refer to corresponding reference.

Modification

Due to the introduction of $\overline{Status_{best}}(t)$, the convergent speed of SEOA is increased significantly , however, it also provides a large probability to fallen into one local optima. In some cases, when all individuals' falls into local optima, there is no any position change, and the best location among entire population $\overline{Status_{best}}(t)$ will be fixed, then, all individuals will converge onto it soon. In this paper, a new strategy is adopted and a group decision mechanism is introduced to overcome this problem. Group decision making (Hu and Yang, 2002; Schermerhorn et al., 2000) is that people make action plan and execute it to achieve certain goals, which is the process of solving problem while raising a question and anglicizing it. It includes four basic elements of decision makers, decision-making basis, decision-making goals, decision making scheme. Decision-making process is the process that the decision-makers find out the problems through investigation and research then determine the decision making goals and design the decision-making scheme, and eventually implement it. When Boyd and Richardson researched the decision-making of human, they proposed the concept of individual learning and sharing culture. In the decision making process, people use two kinds of information: the first one is individual own information, while another one is other individuals' information.

In other words, when people make decision, they do not only make use of their own information but other individuals' information. Inspired by this phenomenon, a group decision strategy in which a new position is estimated in each iteration with different linear combination of current positions of all individuals.

$$\overline{Status_{GD}}(t) = \sum_{\varepsilon=1}^{m} q_{\varepsilon}(t)\overline{x_{\varepsilon best}}(t) \tag{14}$$

Where $q_s(t)$ is the inertia weight at time t. It's obvious that the proper selection of these inertia weight may avoid the information lost. For individual j, the most important information is its current position $\overline{x_j}(t)$, then; the inertia weight $q_s(t)$ is defined as follows:

$$q_s(t) = \frac{e^{\pi s(t)}}{\sum_{h=1}^{m} e^{\pi h(t)}} \tag{15}$$

The current fitness value order j (t) is introduced to extraction the information hidden behind $\overline{x_j}(t)$:

$$\pi_j(t) = \frac{f_{worst} - f(\overline{x_j}(t))}{f_{worst} - f_{best}} \tag{16}$$

Where

$$f_{worst}(t) = \arg\max\{f(\overline{x_j}(t) \mid f = 1,2,...,n)\}$$

and

$$f_{best}(t) = \arg\min\{f(\overline{x_j}(t) \mid f = 1,2,...,n)\}$$

Are the worst and best fitness values of the current positions, respectively.

RESULTS AND DISCUSSION

Simulation

To testify the performance of proposed variant SEOA-GD, four typical unconstraint numerical benchmark functions are chosen, and compared with standard particle swarm optimization (SPSO), modified particle swarm optimizxation with time-varying accelerator coefficients (MPSO-TVAC) (Ratnaweera et al., 2004) and the standard version of SEOA. More details about the test suits can be found in (Yao et al., 1999):

Sphere model

$$f_1(x) = \sum_{j=1}^{n} x_j^2$$

Where $|x_j| \le 100.0$, and

$$f_1(x^*) = f_1(0,0,...,0) = 0.0$$

Rosenbrock function

$$f_2(x) = \sum_{j=1}^{n-1} [100(x_{j+1} - x_j^2)^2 + (x_j - 1)^2]$$

where$|x_j| \le 30.0$, and

$$f_2(x^*) = f_1(0,0,...,0) = 0.0$$

Penalized function1

$$f_3(x) = \frac{\pi}{n}\{10\sin^2(\pi y_1) + \sum_{j=1}^{n-1}(y_j - 1)^2.[1 + 10\sin^2(\pi y_{j+1})] + (y_n - 1)^2\} + \sum_{j=1}^{n} u(x_j, 10, 100, 4)$$

Where $|x_j| \le 50.0$, and

Penalized function 2

$$f_{13}(x) = 0.1\left\{\sin^2(\pi 3x_1) + \sum_{i=1}^{n-1}(x_i - 1)^2[1 + \sin^2(3\pi x_{i+1})] + (x_n - 1)^2[1 + \sin^2(2\pi x_n)]\right\} + \sum_{i=1}^{n} u(x_i, 5, 100, 4)$$

Where $|x_j| \le 50.0$, and

$$u(x_i, a, k, m) = \begin{cases} k(x_i - a)^m, x_i > a, \\ 0, -a \le x_i \le a, \\ k(-x_i - a)^m, x_i < -a. \end{cases}$$

$$y_i = 1 + \frac{1}{4}(x_i + 1)$$

$$f_4(x^*) = f_4(1,1,...,1) = 0.0$$

The inertia weight w is decreased linearly from 0.9 to 0.4 for SPSO and MPSO-TVAC, accelerator coefficients c_1

Table 1. Comparison results for sphere model.

Dim	Alg	Mean	STD
30	SPSO	1.1470e-009	1.9467e-009
	MPSO-TVAC	4.1626e-030	1.2140e-029
	SEOA	2.9026e-010	2.4315e-010
	SEOA-GD	5.5450e-023	7.9696e-023
50	SPSO	1.6997e-007	2.2555e-007
	MPSO-TVAC	1.0330e-012	3.7216e-012
	SEOA	3.1551e+001	2.0241e-010
	SEOA-GD	1.4179e-033	3.8133e-033
100	SPSO	3.0806e-004	3.6143e-004
	MPSO-TVAC	1.4014e-004	3.0563e-004
	SEOA	1.4301e-009	7.0576e-010
	SEOA-GD	4.6252e-055	1.5525e-054
150	SPSO	1.4216e-002	8.3837e-003
	MPSO-TVAC	3.9445e-001	1.7831e+000
	SEOA	3.3950e-000	1.4518e-009
	SEOA-GD	9.6380e-073	2.9405e-072
200	SPSO	1.5234e-001	1. 1698e-001
	MPSO-TVAC	2.1585e-001	4.1999e-001
	SEOA	7.2473e-009	3.1493e-009
	SEOA-GD	1.8304e-087	7.1947e-087
250	SPSO	1.0056e+000	1.0318e+000
	MPSO-TVAC	8.1591e-001	3.8409e+000
	SEOA	1.4723e-008	5.4435e-009
	SEOA-GD	4.7974e-098	2.6253e-097
300	SPSO	1.0370e+001	2.2117e+001
	MPSO-TVAC	3.1681e+000	1.2412e+001
	SEOA	2.0420e-008	6.4868e-009
	SEOA-GD	7.5014e-108	4.0939e-107

and c_2 are both set to 2.0 for SPSO, as well as in MPSO-TVAC, c_1 decreases from 2.5 to 0.5, while c_2 increases from 0.5 to 2.5. Total individuals are 100, and the velocity threshold $v_{\max}$ is set to the upper bound of the domain. The dimensionality is 30, 50, 100, 150, 200, 250 and 300. In each experiment, the simulation run 30 times, while each times the largest iteration is 50 times dimension, for example, the largest iteration is 1500 for dimension 30. For SEOA, all parameters are used the same as Cui et al. (2010).

The comparison results of these four famous benchmarks are listed as Tables 1 to 4, while Figures 1 to 4 verify the dynamic behavior and 20 sample points are selected within the same intervals. In these points, the average best fitness of historical best position of the swarm of all 30 runs are computed and plotted. Sphere model is a uni-modal benchmark, in Table 1, the performance of SEOA-GA is always superior to other three algorithms including SPSO, MPSO-TVAC and SEOA. From Figure 1, we also find the group decision mechanism provides more chances to enter the global optima. Rosenbrock is a famous multi-modal function with only a few local optimums. From Table 2 and Figure 2, the performance of SEOA-GD is also the best one, its performance is slowly changed with the increased dimension. Two penalized functions are famous multi-modal functions with many local optimums. Because there are too many local optimums, the general stochastic algorithm cannot achieve the global position generally. In Tables 4 and 5 the performance of SEOA-GD is the best one with the higher dimension especially with penalized function 2. Based on the above analysis, we can draw the following conclusion: that SEOA-GD is the most stable and effective among four stochastic optimization algorithms. It is especially suit for high-dimensional cases.

Conclusion

In standard version of social emotional optimization algorithm, all individuals' decision is influenced by the

Table 2. Comparison Results for Rosenbrock

Dimension	Algorithm	Mean value	Standard variance
30	SPSO	5.6170e+001	4.3585e+001
	MPSO-TVAC	3.3589e+001	4.1940e+001
	SEOA	4.7660e+001	2.8463e+001
	SEOA_GD	2.6613e+001	1.5519e-001
50	SPSO	1.1034e+002	3.7489e+001
	MPSO-TVAC	7.81256e+001	3.2497e+001
	SEOA	8.7322e+001	7.4671e+001
	SEOA_GD	4.6391e+001	1.5758e-001
100	SPSO	4.1064e+002	1.0585e+002
	MPSO-TVAC	2.8517e+002	9.8129e+001
	SEOA	1.3473e+002	5.4088e+001
	SEOA_GD	9.5756e+001	1.3983e-001
150	SPSO	8.9132e+002	1.6561e+002
	MPSO-TVAC	5.4671e+002	6.4228e+001
	SEOA	2.2609e+002	9.6817e+001
	SEOA_GD	1.4519e+002	9.7379e-002
200	SPSO	2.9071e+003	5.4259e+002
	MPSO-TVAC	8.0076e+002	2.0605e+002
	SEOA	2.9250e+002	9.2157e+001
	SEOA_GD	1.9465e+002	1.1710e-001
250	SPSO	7.4767e+003	3.2586e+003
	MPSO-TVAC	1.3062e+003	3.7554e+002
	SEOA	3.4268e+002	9.0458e+001
	SEOA_GD	2.4408e+002	8.4010e-002
300	SPSO	2.3308e+004	1.9727e+004
	MPSO-TVAC	1.4921e+003	3.4572e+002
	SEOA	3.8998e+002	5.1099e+001
	SEOA_GD	2.9349e+002	9.9428e-002

Table 3. Comparison results for penalized function 1.

Dimension	Algorithm	Mean value	Standard variance
30	SPSO	6.7461e-002	2.3159e-001
	MPSO-TVAC	1.8891e-017	6.9757e-017
	SEOA	3.9296e-011	9.4142e-011
	SEOA_GD	3.9891e-009	7.0974e-009
50	SPSO	5.4175e-002	6.7157e-002
	MPSO-TVAC	3.4248e-002	8.1985e-002
	SEOA	7.5523e-009	4.0782e-008
	SEOA_GD	1.9838e-009	1.1479e-009
100	SPSO	2.4899e+000	1.2686e+000
	MPSO-TVAC	2.3591e-001	1.9999e-001
	SEOA	2.3365e-006	1.2515e-005
	SEOA_GD	1.6989e-009	5.4890e-010
150	SPSO	9.4218e+000	4.2934e+000

Table 3 Contd.

	MPSO-TVAC	4.0496e-001	2.9981e-001
	SEOA	2.6478e-005	1.2041e-004
	SEOA_GD	2.0364e-009	7.0240e-010
200	SPSO	2.8059e+001	1.3881e+001
	MPSO-TVAC	5.7757e-001	2.4178e-001
	SEOA	2.2922e-003	7.6479e-003
	SEOA_GD	2.4934e-009	5.8268e-010
250	SPSO	1.1076e+002	1.9090e+002
	MPSO-TVAC	7.8355e-001	3.2579e-001
	SEOA	2.3115e-003	9.9187e-003
	SEOA_GD	3.1195e-009	7.1319e-010
300	SPSO	5.3088e+002	9.0264e+002
	MPSO-TVAC	4.2045e+000	3.0387e+000
	SEOA	1.7835e-003	5.0264e-003
	SEOA_GD	3.7902e-009	7.9457e-010

Table 4. Comparison results for penalized function 2.

Dimension	Algorithm	Mean value	Standard variance
30	SPSO	5.4943e-004	2.4568e-003
	MPSO-TVAC	9.3610e-027	4.1753e-026
	SEOA	9.7047e-012	5.7058e-012
	SEOA_GD	5.5436e-008	5.2668e-008
50	SPSO	6.4279e-003	1.0769e-002
	MPSO-TVAC	4.9271e-002	2.0249e-001
	SEOA	2.5388e-011	4.0780e-011
	SEOA_GD	6.6033e-008	2.7639e-008
100	SPSO	3.8087e+001	1.8223e+001
	MPSO-TVAC	3.7776e-001	6.1358e-001
	SEOA	2.6187e-010	5.3124e-010
	SEOA_GD	2.3036e-007	2.2444e-007
150	SPSO	1.6544e+002	5.5689e+001
	MPSO-TVAC	1.2655e+000	1.4557e+000
	SEOA	1.8553e-009	2.9614e-009
	SEOA_GD	5.0978e-007	4.0580e-007
200	SPSO	1.8029e+003	2.8233e+003
	MPSO-TVAC	2.3221e+000	1.5383e+000
	SEOA	3.6341e-008	7.0038e-008
	SEOA_GD	9.7898e-007	2.6837e-007
250	SPSO	6.7455e+003	9.5733e+003
	MPSO-TVAC	2.8991e+000	1.3026e+000
	SEOA	1.8303e-007	1.5719e-007
	SEOA_GD	3.6700e-006	1.1625e-005
300	SPSO	3.2779e+004	4.4431e+004
	MPSO-TVAC	3.7344e+000	2.6830e+000
	SEOA	2.9760e-006	1.2540e-005
	SEOA_GD	2.8533e-006	1.6203e-006

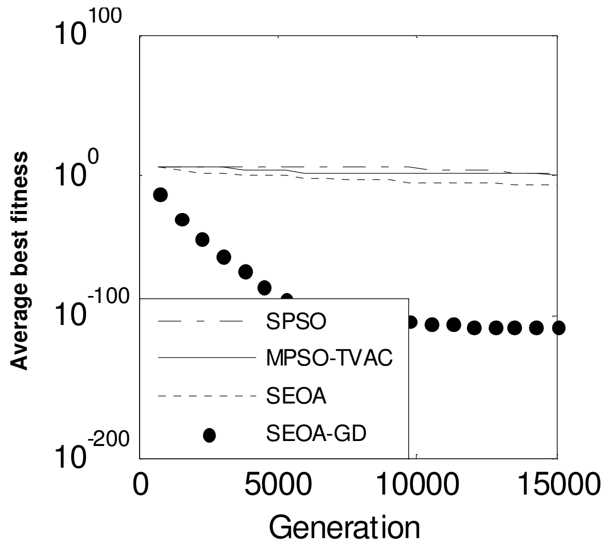

Figure 1. Dynamic comparison for sphere.

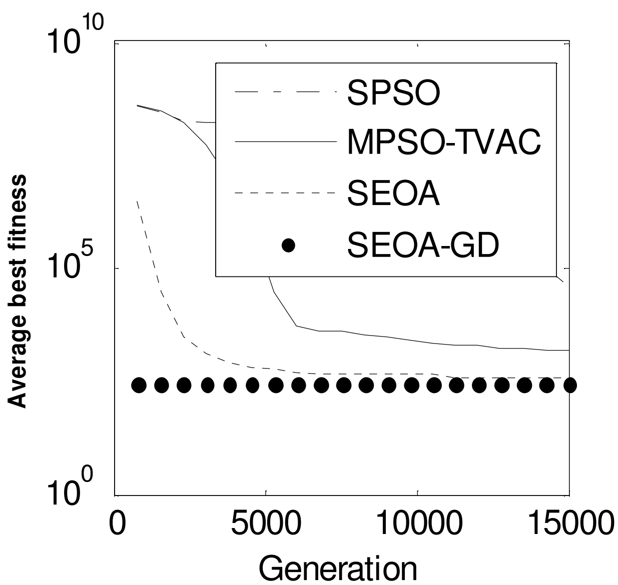

Figure 2. Dynamic comparison for rosenbrock.

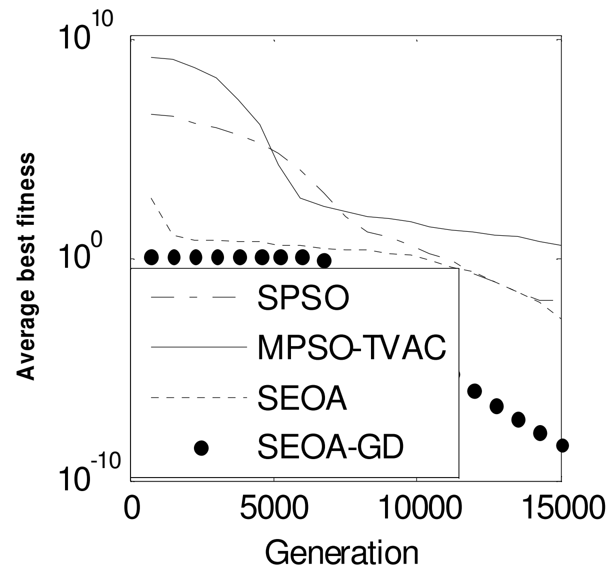

Figure 3. Dynamic comparison for penalized function1.

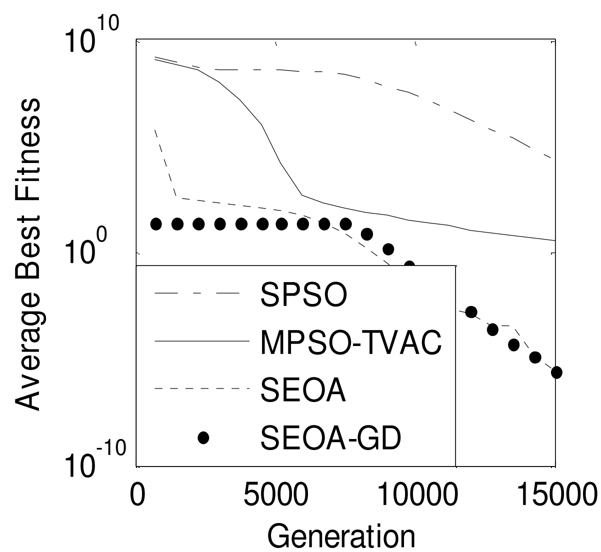

Figure 4. Dynamic Comparison for Penalized Function2.

best position found by entire swarm. However, this position may provide a wrong search direction in many cases. Therefore, this paper incorporates a new strategy, group decision mechanism into the methodology of SEOA to overcome this shortcoming, in which a convex combination of all individual's positions are used, and an estimated position is used to provide the guidance. To test the performance of SEOA-GD, four famous benchmarks are chosen, and compared with other three swarm intelligent algorithms. Simulation results show this new variant is effective and efficient especially for high-dimensional cases. A future research topic includes the application of SEOA-GD to the other problems.

ACKNOWLEDGEMENTS

This paper were supported by the Key Project of Chinese Ministry of Education under Grant No.209021, the National Natural Science Foundation of China under Grant No.61003053, 60775035, 60903141 and 60970088, the Major State Basic Research Development Program of China under Grant No.2007CB311004, the National Science and Technology Support Plan under Grant No.2006BAC08B06 and the Major Program of National Natural Science Foundation of China under Grant No.60933004.

REFERENCES

He S, Wu QH, Saunders JR (2006) Group search optimizer an optimization algorithm inspired by animal searching behavior. IEEE Int. Conf. Evol. Comp., pp. 973-990.

Xie LP, Tan Y, Zeng JC, Cui ZH (2010) Artificial physics optimization: a brief survey. Int. J. Bio-inspired Comp., 2(5): 291-302.

Yang XS (2010) Firefly algorithm, stochastic test functions and design optimization. Int. J. Bio-inspired Comp., 2(2): 78-84.

Laalaoui Y, Drias H (2010) ACO approach with learning for preemptive scheduling of real-time tasks. Int. J. Bio-inspired Comp., 2(6): 383-394.

Abraham S, Sanyal S, Sanglikar M (2010) Particle swarm optimisation based Diophantine equation solver, Int. J. Bio-inspired Comp., 2(2): 100-114.

Yuan DL, Chen Q (2010) Particle swarm optimisation algorithm with forgetting character. Int. J. Bio-inspired Comp., 2(1): 59-64.

Lu JG, Zhang L, Yang H, Du J (2010) Improved strategy of particle swarm optimisation algorithm for reactive power optimization. Int. J. Bio-inspired Comp., 2(1): 27-33.

Upendar J, Singh GK, Gupta CP (2010) A particle swarm optimisation based technique of harmonic elimination and voltage control in pulse-width modulated inverters. Int. J. Bio-inspired Comp., 2(1): 18-26.

Cui ZH, Cai XJ (2010) Using social cognitive optimization algorithm to solve nonlinear equations. 9th IEEE Int. Conf. on Cog. Inf. (ICCI 2010), pp. 199-203.

Chen YJ, Cui ZH, Zeng JH (2010). Structural optimization of lennard-jones clusters by hybrid social cognitive optimization algorithm. 9th IEEE Int. Conf. Cog. Inf. (ICCI 2010)., pp. 204-208.

Cui ZH, Shi ZZ, Zeng JC (2010) Using social emotional optimization algorithm to direct orbits of chaotic systems, 1st Int. Conf. Swarm, Evol. Memetic Comput. (SEMCCO2010)., pp. 389-395.

Wei ZH, Cui ZH, Zeng JC (2010) Social cognitive optimization algorithm with reactive power optimization of power system, 2010 Int. Conf. Computational Aspects of Social Networks (CASoN2010), pp. 11-14.

Xu YC, Cui ZH, Zeng JC (2010) Social emotional optimization algorithm for nonlinear constrained optimization problems, 1st Int. Conf. on Swarm, Evol. and Memetic Computing (SEMCCO2010), pp. 583-590.

Cai XJ, Cui ZH, Zeng JC, Tan Y (2008) Particle swarm optimization with self-adjusting cognitive selection strategy, Int. J. of Innovative Computing, Inf. Control., 4(4): 943-952.

Hu CJ, Yang YK (2002) Organizational Behavior, Fudan university press.

Schermerhorn HR, Hunt JG, Richard NO (2000) Organizational Behavior. The Publishing House of Economic Science.

Ratnaweera A, Halgamuge SK, Watson HC (2004) Self-organizing hierarchical particle swarm opitmizer with time-varying acceleration coefficients, IEEE Trans. Evol. Comp., 8(3): 240-255.

Yao X, Liu Y, Lin GM (1999) Evolutionary programming made faster, IEEE Trans. Evol. Comp., 3(2): 82-102.