Particle Swarm Optimization Based on Punctuated-equilibrium Model

Zhenzhou An¹*, Jun Zhang¹, Yang Yang¹ and Xiaoyan Wang²

¹School of Mathematics and Information Technology, Yuxi Normal University, Yuxi, Yunnan, China
²School of Physics and Electronic Engineering, Yuxi Normal University, Yuxi, Yunnan, China

*Corresponding author. Email: an@yxnu.edu.cn

Abstract. This paper presents a modified particle swarm optimization, named as punctuated-equilibrium particle swarm optimization (PEPSO). This method refers to punctuated-equilibrium Model (PEM) which is a pattern of group development in organizational behavior. PEM uses the long-term equilibrium phase and the short-term abrupt phase to solve the problem of group stagnation. The present work mathematically modelled this alternating process. The efficiency of the proposed PEPSO was evaluated using CEC 2014 benchmark functions. The experiments showed that PEPSO could solve premature convergence and had more good convergence accuracy than PSO on some test functions. Furthermore, it was also confirmed that the swarm was divided into different groups and the individuals of every group almost acted in unison. This provides a good explanation between PSO and organizational behavior from a new experimental perspective.

Keywords: particle swarm optimization, organizational behavior, punctuated-equilibrium model.

1. Introduction

Particle Swarm Optimization (PSO) is the study of swarm behavior in intelligent computing. It mainly studies individuals, swarm, and neighbor topology [1]. PSO mainly solves the problem of the explorative and exploitative capability of swarm [2]. It sometimes suffers from premature convergence, especially in the complex multi-modal problems. Therefore, avoiding the local optima and maintaining a population’s diverse have become the goals of many researches. Recently, multi-swarm and multi-role techniques [3-7] have been proposed to achieve these goals. The whole population was divided into a large number sub-swarms and the sub-swarms were regrouped frequently by using various regrouping schedules in Ref. [3]. The concept of family was introduced in the PSO and analyzed the convergence of algorithm theoretically in Ref. [4, 5]. Three roles of leader, rambler, and follower were assigned for particles at each generation based on their fitness in Ref. [6]. The problem of group stagnation has been studied using different methods.

Organizational behavior investigates the impact that individuals, groups, and structure have on behavior within organizations. It applies such knowledge in order to make organizations work more effectively [8]. Punctuated-equilibrium Model (PEM) is a pattern of group development in organizational behavior [9, 10]. PEM has achieved success on many real applications, such as
international organizations [11], tumor evolution [12], policy change [13], and software development project [14].

PEM has an important characteristic that the long-term equilibrium phase and the short-term abrupt phase alternate. In this research, inspired by this characteristic, we propose particle swarm optimization based on punctuated-equilibrium model (PEPSO) in which the abrupt phase will happen when the performance of swarm don’t be improved. The aim of the transition is to help the population search for new regions of the search space while retaining the current best result.

The rest of this paper is organized as follows. Section 2 describes the framework of the details of PEPSO algorithm. Extensive experiments about PEPSO on the CEC2014 test suite [15] are introduced in Section 3. Moreover, group characteristics involved in PEPSO are also detailed in this section. Finally, conclusions are given in Section 4.

2. Method

2.1. PSO

In PSO, each particle characterizes by two variables \( x_i \) and \( v_i \). they are updated according to the following equations:

\[
\begin{align*}
\dot{v}_i(t + 1) &= \omega v_i(t) + c_1 \phi_1 (p_i(t) - x_i(t)) + c_2 \phi_2 (g(t) - x_i(t)) \\
\dot{x}_i(t + 1) &= x_i(t) + v_i(t + 1)
\end{align*}
\]

where \( t \) is the iteration; \( \omega \) is inertia factor; \( c_1 \) and \( c_2 \) are affect acceleration; \( \phi_1 \) and \( \phi_2 \) are random variables in the range (0,1); \( p_i \) is the personal best position of the \( i \)-th particle; \( g \) is the best position of all the particles [1].

A particle finds a potential solution through itself and the best position of all the particles. There is no direct connection between particle and particle.

2.2. Punctuated-equilibrium model

In organizational behavior, the evolution of groups has a predictable sequence. Punctuated-equilibrium Model (PEM) is a pattern of group development [8, 9, 10]. These groups have their own unique sequencing of actions:

(1) Sets the group’s direction;
(2) The first phase of group activity
   • Group activity is one of inertia;
(3) Transition
   • A transition takes place at the end of the first phase, which occurs exactly when the group has used up half its allotted time;
   • A transition initiates major changes;
(4) A second phase of group activity
   • Inertia follows the transition;
   • The group’s last phase is characterized by markedly accelerated activity [8].

PEM can be used to solve the problem of group stagnation through the transition.

2.3. PEPSO MODEL

2.3.1. PEPSO model design. PEPSO Model characterizes groups as proceeding through the grouping, optimizing, balancing, transition, optimizing and balancing operations.

Grouping operation: particle swarm can be divided into different small groups. The way of random grouping is being used.
Optimizing operation: group development is organized according to Eqs. (3) and (4) at the first phase. The $i$-th particle belongs to the $k$-th group, and the movement of the $i$-th particle is closely related to the members of the $k$-th group.

$$v_i(t + 1) = \omega v_i(t) + \sum_{i \in k} c_i \varphi_1 (p_i(t) - x_i(t)) + c_g \varphi_2 (g(t) - x_i(t))$$ (3)

$$x_i(t + 1) = x_i(t) + v_i(t + 1)$$ (4)

where $c_i = 1$/the number of members of the $k$-th group, $c_g = 1$/the number of average members of all groups.

Balancing operation: if the best fitness value of swarm can’t be improved within $m$ iterations, the first stage ends.

Transition operation: recording the global optimal result and make it enter the second phase. The other particles should be re-initialized. The swarm happens major changes and enters into the second phase.

Optimizing operation: group development is organized according to Eqs. (3) and (4) at the second phase.

Balancing operation: if the best fitness value of swarm can’t be improved within $m$ iterations, the second stage ends.

2.3.2. Main framework. The main framework of PEPSO is shown in Table 1.

| Algorithm. The procedure of PEPSO |
|-----------------------------------|
| **1**: Population parameters initialization  |
| Initialize $N$ individuals $[X_1, X_2, ..., X_N], [V_1, V_2, ..., V_N]$ ($X_i = (x_{i1}, x_{i2}, ..., x_{in}), V_i = (v_{i1}, v_{i2}, ..., v_{in})$) with the $n$ dimension; |
| **2**: Group parameters initialization  |
| $N = \sum_{i=1}^{\text{num}} \text{group\_num}(i), c_i = 1/\text{group\_num}(i), c_g = \text{mean}(1/\text{group\_num}(i)), (i=1,2,\ldots,\text{num})$. |
| **3**: Balancing time: $m$  |
| **4**: The first stage |
| **4.1**: Do  |
| **4.2**: For each group  |
| **4.3**: Update the particle’s velocity and position by using Eqs. (3) and (4), respectively.  |
| **4.4**: Determine the personal best position, $p_i$  |
| **4.5**: Determine each group’s best position, $g_p$  |
| **4.6**: EndFor  |
| **4.7**: Determine the current global best position and velocity, $pg_1$, $vg_1$  |
| **4.8**: While $pg_1(t) \neq pg_1(t-m)$  |
| **5**: Transition operation  |
| **5.1**: $X_i = pg_1; V_i = vg_1$  |
| **5.2**: Initialize $N$-1 individuals $[X_2, X_3, ..., X_N], [V_2, V_3, ..., V_N]$ ($X_i = (x_{i1}, x_{i2}, ..., x_{in}), V_i = (v_{i1}, v_{i2}, ..., v_{in})$) with the $n$ dimension; |
| **6**: The second stage |
| **6.1**: Do  |
| **6.2**: For each group  |
| **6.3**: Update the particle’s velocity and position by using Eqs. (3) and (4), respectively.  |
| **6.4**: Determine the personal best position, $p_i$  |
| **6.5**: Determine each group’s best position, $g_p$  |
| **6.6**: EndFor  |
| **6.7**: Determine the current global best position and velocity, $pg_2$, $vg_2$  |
| **6.8**: While $pg_2(t) \neq pg_2(t-m)$  |

Table 1. The procedure of PEPSO.
3. Experiments

3.1. Test problems and parameter setting
To validate the performance of PEPSO, we test it on a set of benchmark functions from CEC2014 test suits [15]. The parameters of PSO [1] are: $c_1 = c_2 = 2$, $\omega$ is from 0.9 to 0.4 according to the linear decrease. In order to facilitate the comparison, the swarm which has 100 particles is divided into 20 groups ($num = 20$) and every group has 5 particles ($group_num(i) = 5$) in PEPSO. The parameters of PEPSO are: $c_i = c_g = 1/5$, $D=10$.

$FES$ is the number of iterations and its value is from 1 to $MaxFES = 10000$. $FEScut$ is the values of $(0.0001, 0.001, 0.01, 0.02, 0.03, 0.04, 0.05, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0) \times MaxFES$. All algorithms are implemented in MATLAB platform and 50 independent runs are performed for each algorithm. 17 error values ($F_i(x) - F_i(x^*)$) at $FEScut$ are recorded for each function for each run.

3.2. Experiment results
When $MaxFES$ is equal to 10000, the transition is happened with $FES = MaxFES/2$. Sort the error values achieved after $MaxFES$ in 50 runs, the best, worst, mean, median, standard variance of 10-demensional functions are listed in Table 2. The bold value is the best result for the same test function using different algorithms. The results show that the mean error values of PEPSO have smaller values at $MaxFES$ than PSO on $f_5, f_6, f_{10}, f_{13}$.

17 error values ($F_i(x) - F_i(x^*)$) at $FEScut$ are shown in Fig.1. The results show that PEPSO has more good convergence accuracy and evolution velocity than PSO on $f_5, f_6, f_9, f_{10}$.

Table 2. Results of the error values at MaxFES by PSO and PEPSO.

| Fun | Algorithm | Best      | Worst     | Median    | Mean       | Std       |
|-----|-----------|-----------|-----------|-----------|------------|-----------|
| $f_5$ | PSO       | 20.02777024 | 20.27117763 | 20.15725084 | 20.16258268 | 0.057886116 |
|      | PEPSO     | 0         | 20.25172839 | 5.68E-14   | 1.211125304 | 4.84245991 |
|      | $f_6$     | $4.52E-07$ | 2.267319646 | 0.000647403 | 0.347079682 | 0.685281784 |
|      | PSO       | 4.52E-07  | 0.034847109 | 2.08E-06   | 0.00086925  | 0.004962296 |
|      | PEPSO     | 4.52E-07  | 0.034847109 | 2.08E-06   | 0.00086925  | 0.004962296 |
|      | $f_9$     | $4.974795285$ | 13.92941672 | 8.954626476 | 9.275431943 | 2.592481609 |
|      | PEPSO     | 5.049696372 | 14.92437074 | 9.126495028 | 9.484488146 | 2.024586083 |
|      | $f_{10}$  | 208498.4139 | 208851.0851 | 208526.5316 | 208568.3709 | 80.99883472 |
|      | PEPSO     | 208494.0327 | 208796.6836 | 208517.1723 | 208537.0011 | 57.14896058 |
|      | $f_{13}$  | $0.221216335$ | 0.503001541 | 0.370847534 | 0.36021257  | 0.068865896 |
|      | PEPSO     | 0.249595562 | 0.423119036 | 0.313740459 | 0.31901002  | 0.036918422 |
When balancing time $m$ is equal to 500 on $f_5$, the processes of 100 particles at different iterations are shown in Fig. 2. To show the changing processes of the fitness values, different colors represent different groups. The results show that the individuals of every group almost act in unison. The fitness values of $g_{best}$ and different particles are shown in Fig. 3. The results show that the $g_{best}$ of the second stage is less than or equal to the $g_{best}$ of the first stage. The specific reason is the $g_{best}$ of the first stage has been maintained and the development of the second stage depends on this value. Furthermore, experiments show that some particles can find better fitness values after the transition.

Figure 1. Results of the error values by PSO and PEPSO.

Figure 2. The fitness values of 100 particles at different iterations. Different colors represent different groups. $m = 500$. 
4. Conclusions
PSO is the study of group behavior in intelligent computing and PEM is a pattern of group development in organizational behavior. PEM can be used to solve the problem of group stagnation. PEM should be referred and introduced to further improve the PSO. The experiments show that PEPSO has more good convergence accuracy and evolution velocity than PSO on some test functions. It is also confirmed that the swarm is divided into different groups and the individuals of every group almost act in unison. This provides a good explanation for the relationship between PSO and organizational behavior.

Acknowledgement
This research was financially supported by the National Science Foundation of China (61563055) and Construction Plan of Key Laboratory of Institutions of Higher Education in Yunnan Province.

References
[1] J. Kennedy, R. Eberhart, Particle swarm optimization, Proceedings of ICNN'95 - International Conference on Neural Networks, IEEE, (1995).
[2] R. Eberhart, Y.H. Shi, Particle swarm optimization: developments, applications and resources, Proceedings of the 2001 Congress on Evolutionary Computation (IEEE Cat. No.01TH8546), IEEE, (2002).
[3] J. Liang, R. Liu, K.J. Yu, B.Y. Qu, Dynamic multi-swarm particle swarm optimization with cooperative coevolution for large scale global optimization, Journal of Software, 29.9 (2018) 2595-2605.
[4] Z.Z. An, J.R. Bai, Y. Ma, N.Y. Jia, X.L. Shi, A family particle swarm optimization based on the animal collective behavior, Appl. Mech. Mater., 513-517 (2014) 2439-2443.
[5] Z.Z. An, X.Y. Wang, X.L. Shi, A study on the convergence of family particle swarm optimization, Mathematical Problems in Engineering: Theory, Methods and Applications, (2017).
[6] X. Xia, Y. Xing, B. Wei, Y. Zhang, L. Gui, A fitness-based multi-role particle swarm optimization, Swarm and Evolutionary Computation, 44 (2018).
[7] C.Y. Qiu, A novel multi-swarm particle swarm optimization for feature selection, Genetic Programming and Evolvable Machines, 1-4 (2019).

[8] S.P. Robbins, T.A. Judge, Organizational Behavior, fourteenth ed., Tsinghua University Press, Bei Jing, 2012.

[9] Gersick, J.G. Connie, Time and transition in work teams: toward a new model of group development, Academy of Management Journal, 31.1 (1988) 9-41.

[10] H. Arrow, M.S. Poole, K.B. Henry, S. Wheelan, R. Moreland, Time, change, and development: the temporal perspective on groups, Small Group Research, 35.1 (2004) 73-105.

[11] M. Lundgren, T. Squatrito, J. Tallberg, Stability and change in international policy-making: a punctuated equilibrium approach, Review of International Organizations, 4 (2017) 1-26.

[12] C.K. Sievers, W.M. Grady, R.B. Halberg, P.J. Pickhardt, New insights into the earliest stages of colorectal tumorigenesis, Expert Rev. Gastroenterol. Hepatol., 11.8 (2017).

[13] D. Beyer, C. Breunig, M. Radojevic, Commentaries on the improvement of china's fair competition review system-based on punctuated equilibrium theory, Price:Theory & Practice, (2018).

[14] A.L. Mcnab, K.A. Basoglu, S. Sarker, Y. Yu, Evolution of cognitive trust in distributed software development teams: a punctuated equilibrium model, Electronic Markets, 22.1 (2012) 21-36.

[15] J.J. Liang, B.Y. Qu, P.N. Suganthan, Problem definitions and evaluation criteria for the CEC 2014 special session and competition on single objective real-parameter numerical optimization, Technical report 201311, Computational Intelligence Laboratory, Zhengzhou University, Zhengzhou China and Technical Report, Nanyang Technological University, Singapore, (2013).