IEICE The Institute of Electronics, Information and Communication Engineers

IEICE Proceeding Series

Proposal of Parameter Setting Method on Independent-minded Particle Swarm Optimization

Haruna Matsushita

Vol. 1 pp. 154-157
Publication Date: 2014/03/17
Online ISSN: 2188-5079

Downloaded from www.proceeding.ieice.org

©The Institute of Electronics, Information and Communication Engineers

Proposal of Parameter Setting Method on Independent-minded Particle Swarm Optimization

Haruna Matsushita†

†Department of Electronics and Information Engineering, Kagawa University
2217–20 Hayashi-cho, Takamatsu, Kagawa, 761–0396 Japan
Email: haruna@eng.kagawa-u.ac.jp

Abstract—This study proposes a setting method of the important parameter which influences the optimization ability on an Independent-minded Particle Swarm Optimization (IPSO). The proposed parameter is a linear function proportional to the simulation step. We confirm that although it is very simple and does not need additional parameters, the proposed IPSO obtains better results than the standard PSO and the conventional IPSO, for the multimodal functions. From these results, we do not need complicated settings of the parameters and can easily use the IPSO.

1. Introduction

Particle Swarm Optimization (PSO) [1] is an optimization algorithm based on a swarm intelligence. Multiple solutions called as "particle" search the optimum solution with flying around search space. Since each particle flies toward its personal best position *pbest* and the best position among the whole swarm *gbest*, all the particles of the standard PSO are fully-connected and always influence each other.

On the other hand, various topological neighborhoods for PSO have been considered [2–6]. In these papers, each particle shares its best position among neighboring particles on the network. It is an application of the network topology to the particle swarm, and investigations of the suitable network for PSO have attracted attention in these years [7, 8].

Our previous study has proposed a novel application of the complex network to PSO; an Independent-minded Particle Swarm Optimization (IPSO) [9]. The most important feature of IPSO is that it is decided stochastically that each particle depends on*gbest* or becomes independent from the swarm and moves depending only on *pbest*. In other words, the particles are not always connected each other, and they act with self-reliance. IPSO was applied to various problems, and it has been confirmed that IPSO is effective for complex problems with numerous local optima [11]. Meanwhile, a cooperativeness coefficient Cp , which is the independence probability of the particles, is the important parameter and influences the performance of IPSO, and it needs careful setting depending on problems.

This study proposes a setting method of the cooperativeness Cp in IPSO. The proposed Cp is a linear function proportional to the generation step and does not need additional parameters. We apply the IPSO using the proposed Cp to various benchmark problems used widely in the literature, and we confirm that the proposed method can obtain better results than the conventional IPSO using Cp set carefully. In addition, we carry out simulations with changing maximum simulation steps and investigate effectiveness and robustness of IPSO with the proposed Cp.

2. Independent-minded Particle Swarm Optimization (IPSO)

In the algorithm of the PSO, multiple potential solutions called "particles" coexist. Each particle i ($i = 1, 2, \cdots, M$) has two information; position and velocity, represented by $\boldsymbol{X}_i = (x_{i1}, \cdots, x_{id}, \cdots, x_{iD})$ and $\boldsymbol{V}_i = (v_{i1}, \cdots, v_{id}, \cdots, v_{iD})$ ($d = 1, 2, \cdots, D$), respectively. At each time step, each particle flies toward its own past best position (*pbest*) and the best position among all particles (*gbest*). In other words, they always influence each other. On the other hand, the particles of IPSO have independence, thus, it is decided stochastically whether they are connected to others at every step. In other words, they are not always affected by the swarm and their *pbest* does not always affect the swarm.

2.1. Algorithm of IPSO

(Step1) (Initialization) Let a generation step $t = 0$. Randomly initialize the particle position $\boldsymbol{X}_i$ ($\boldsymbol{X}_i \in [x_{\min}, x_{\max}]^D$), initialize its velocity $\boldsymbol{V}_i$ to zero, and initialize $\boldsymbol{P}_i = (p_{i1}, p_{i2}, \cdots, p_{iD})$ with a copy of $\boldsymbol{X}_i$. Evaluate the objective function $f(\boldsymbol{X}_i)$ for each particle i and find $\boldsymbol{P}_g$ with the best function value among all the particles.

(Step2) Decide whether each particle i is connected to the others according to rand_i which is a random number ($\in (0, 1)$) for the particle i. *If* $\text{rand}_i \leq C$, *the particle i is connected to other particles. If not, the particle i is isolated from the swarm, then, it and others do not affect each other.* Cp is a constant cooperativeness coefficient which is the independence probability of the particles.

(Step3) Evaluate the fitness $f(\boldsymbol{X}_i)$ for each particle i. Update the personal best position (*pbest*) as $\boldsymbol{P}_i = \boldsymbol{X}_i$ if $f(\boldsymbol{X}_i) < f(\boldsymbol{P}_i)$.

(Step4) Let $\boldsymbol{P}_l$ represents the best position *lbest* with the best *pbest* among particles being connected to others. Update *lbest* $\boldsymbol{P}_l = (p_{l1}, p_{l2}, \ldots, p_{lD})$ according to

$$l = \arg\min_i f(\boldsymbol{P}_i), \quad \text{rand}_i \leq Cp. \tag{1}$$

In other words, even if the $f(\boldsymbol{P}_i)$ is the minimum *pbest* among all the particles, *lbest* is not updated if i is not connected to others.
(Step5) Update $\boldsymbol{V}_i$ and $\boldsymbol{X}_i$ of each particle i according to

$$\boldsymbol{V}_i(t+1) = \begin{cases} w\boldsymbol{V}_i(t) & + c_1\boldsymbol{r}_1(\boldsymbol{P}_i - \boldsymbol{X}_i(t)) \\ & + c_2\boldsymbol{r}_2(\boldsymbol{P}_l - \boldsymbol{X}_i(t)), \ \text{rand}_i \leq Cp \\ w\boldsymbol{V}_i(t) & + c_1\boldsymbol{r}_1(\boldsymbol{P}_i - \boldsymbol{X}_i(t)), \ \text{rand}_i > Cp \end{cases}$$
$$\boldsymbol{X}_i(t+1) = \boldsymbol{X}_i(t) + \boldsymbol{V}_i(t+1) \tag{2}$$

where w is the inertia weight determining how much of the previous velocity of the particle is preserved. c_1 and c_2 are two positive acceleration coefficients, generally $c_1 = c_2$. $\boldsymbol{r}_1$ and $\boldsymbol{r}_2$ are d-dimensional uniform random number vectors from $U(0,1)$. These equations mean that whether each particle is affected by *lbest* is decided at random with the cooperativeness Cp. When $Cp = 0$, all the particles move depending only on own *pbest*, and when $Cp = 1$, the algorithm is completely the same as the standard PSO.
(Step6) Let $t = t + 1$ and go back to (Step2) if t has not yet reached the maximum generation step.

2.2. Influence of Cooperativeness Cp on optimization performance

In order to investigate the influence of the cooperativeness Cp on optimization performance, our previous study applied various benchmark problems containing unimodal functions and multimodal functions. In the results with various Cp, $Cp = 1.0$ obtained the best result on the unimodal function. In contrast, on the multimodal function, IPSO obtained more effective results when the particles were little affected by *gbest*, than in case of fully-connected ($Cp = 1.0$). Furthermore, it was clear that IPSO is effective method for the multimodal functions. On the other hand, because the results depend on the kind of problems, it is important to set the value of Cp appropriately.

3. Consideration of appropriate value of Cooperativeness Cp.

This study proposes the setting method of appropriate Cooperativeness Cp in IPSO. From characteristics of IPSO described by Eq. (2), we consider relationship between Cp and the performance as follows.

Small Cp:
Searching ability around each *pbest* becomes high because the particles are attracted only to *pbest*. Diversity is high.
Large Cp:
Searching ability around each *lbest* becomes high because the influence of *lbest* grows. Diversity is low.

From these reasons, in early stage of the simulation, it is effective to grow the diversity (as small Cp) because global search is efficient. In contrast, in late stage of the simulation, it is effective to increase the convergence speed by growing the searching ability around *lbest* (as large Cp).

Based on these considerations, we define the Cooperativeness Cp as following equation.

$$Cp(t) = \frac{1}{T}t, \tag{3}$$

This is a linear function proportional to the generation step, and although it is very simple and does not need additional parameters, it satisfies the consideration described above.

4. Simulation experiments

In order to investigate the proposed Cooperativeness Cp, we apply it to four benchmark problems summarized in Table 1. f_1 is an unimodal function, and f_2–f_4 are multimodal functions with numerous local minima. The optimum solution $\boldsymbol{X}^*$ of all the functions are $[0, 0, \cdots, 0]$, and its optimum value $f(\boldsymbol{X}^*)$ is 0. All the functions have D variables, in this study, $D = 30$. The proposed IPSO is compared with the standard PSO and IPSO. For all PSOs in all the simulations, the population size M is set to 36, and the parameters are set as $w = 0.7$ and $c_1 = c_2 = 1.6$. The Cooperativeness Cp of the conventional IPSO are set as $Cp = 1.0$, 0.6, 0.4 and 0.06 which are appropriate values for f_1, f_2, f_3 and f_4, respectively [10]. The maximum generation is set at 3000, and the results are evaluated in an achievement rate of the criterion attainment over 100 trials.

Table 2 summarizes the mean fitness $f(\boldsymbol{P_g})$, the best fitness and the achievement rate[%] of the standard PSO, the conventional IPSO (const. Cp) and the proposed IPSO (time-variable Cp). We can see that in the unimodal function f_1, the standard PSO, which is exactly same as IPSO with $Cp = 1$, obtained the best result. However, since the proposed IPSO also obtained the perfect achievement rate, it can obtain enough result as the optimization result. In the results of the multimodal functions f_2 and f_3, because PSO using the time-variable Cp obtained the best results, we can conclude that the linear function proportional to the simulation step is effective setting method of the Cooperativeness Cp. We do not need complicated settings of the parameters which influences the optimization performance, then we can easily use the IPSO by using the time-variable Cp. In addition, because IPSO with time-variable Cp can obtain better results than IPSO with the constant Cp carefully set, it is effective for escaping from the local optima to vary Cp during the simulation.

Next, Fig. 1 shows convergence of three PSOs. We can see that IPSOs obtained better results than the standard PSO, on the multimodal functions, and IPSO with time-variable Cp converged with same speed as the conventional IPSO. From these results, we can conclude that the pro-

Table 1: Four Test Functions.

Function name	Test Function	Initialization Space	Criterion
Sphere;	$f_1(\boldsymbol{X}) = \sum_{d=1}^{D} x_d^2,$	$\boldsymbol{X} \in [-5.12, 5.12]^D,$	0.01
Rastrigin;	$f_2(\boldsymbol{X}) = \sum_{d=1}^{D} \left(x_d^2 - 10\cos(2\pi x_d) + 10\right),$	$\boldsymbol{X} \in [-5.12, 5.12]^D,$	50
Ackley;	$f_3(\boldsymbol{X}) = \sum_{d=1}^{D-1} \Big(20 + e - 20e^{-0.2\sqrt{0.5(x_d^2+x_{d+1}^2)}} - e^{0.5(\cos(2\pi x_d)+\cos(2\pi x_{d+1}))}\Big),$	$\boldsymbol{X} \in [-30, 30]^D,$	1.0
Stretched V;	$f_4(\boldsymbol{X}) = \sum_{d=1}^{D-1} (x_d^2 + x_{d+1}^2)^{0.25} \left(1 + \sin^2(50(x_d^2 + x_{d+1}^2)^{0.1})\right),$	$\boldsymbol{X} \in [-10, 10]^D$	10

Table 2: Comparison results of 3 PSOs on 4 test functions. IPSO used Cp = 1.0, 0.6, 0.4 and 0.06 for f_1 f_2 f_3 and f_4, respectively.

f		PSO	IPSO (const. Cp)	IPSO (time-variable Cp)
f_1	Mean	3.38e-48	5.10e-50	1.77e-26
	Min	2.39e-57	1.44e-55	9.62e-29
	Achievement	100%	100%	100%
f_2	Mean	63.40	39.83	**34.92**
	Min	34.82	14.92	15.92
	Achievement	37%	89%	95%
f_3	Mean	73.14	12.84	**9.02**
	Min	5.16	4.09e-11	5.24e-14
	Achievement	0%	52%	32%
f_4	Mean	21.76	9.36	**7.01**
	Min	6.27	2.37	0.80
	Achievement	6%	62%	79%

posed IPSO can realize the searching ability of the conventional IPSO.

5. Conclusions

This study has proposed the setting method of the important parameter which influences the optimization ability on the independent-minded particle swarm optimization (IPSO). The proposed parameter is the linear function proportional to the simulation step. Although it is very simple and does not need additional parameters, the proposed IPSO obtained better results than the conventional IPSO, for the multimodal functions. We do not need the complicated settings of the parameters and can easily use the IPSO. By using IPSO, we can obtain significantly effective performance, compared with the standard PSO.

Acknowledgments

This work was supported by KAKENHI 24700226.

References

[1] J. Kennedy and R. C. Eberhart, "Particle swarm optimization," in *Proc. of IEEE. Int. Conf. on Neural Netw.*, pp. 1942–1948, 1995.

[2] J. Kennedy and R. Mendes, "Population structure and particle swarm performance," in *Proc. of Cong. on Evolut. Comput.*, pp. 1671–1676, 2002.

[3] R. Mendes, J. Kennedy and J. Neves, "The Fully Informed Particle Swarm: Simpler, Maybe Better," in *IEEE Trans. Evolut. Comput.*, vol. 8, no.3, pp. 204–210, June 2004.

[4] J. Lane, A. Engelbrecht and J. Gain, "Particle Swarm Optimization with Spatially Meaningful Neighbors," in *Proc. of IEEE Swarm Intelligence Symposium*, pp. 1–8, 2008.

[5] S. B. Akat and V. Gazi, "Particle Swarm Optimization with Dynamic Neighborhood Topology: Three

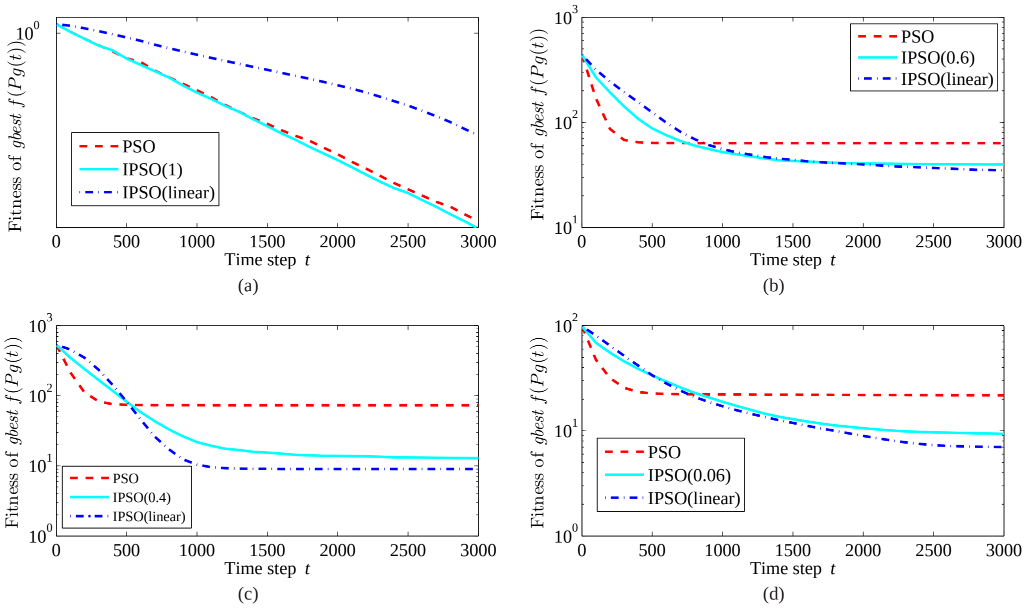

Figure 1: Mean $f(\boldsymbol{P}_g)$ of 100 trials, depending on the time step t. (a) Sphere function. (b) Rastrigin function. (c) Ackley's function. (d) Stretched V sine wave function.

Neighborhood Strategies and Preliminary Results," in *Proc. of IEEE Swarm Intelligence Symposium*, pp. 1–8, 2008.

[6] H. Matsushita and Y. Nishio, "Network-Structured Particle Swarm Optimizer with Various Topology and its Behaviors," in *Lecture Notes in Computer Science*, vol. 5629, pp. 163–171, 2009.

[7] J. Kennedy, "Small worlds and mega-minds: effects of neighborhood topology on particle swarm performance," in *Proc. of Cong. on Evolut. Comput.*, pp. 1931–1938, 1999.

[8] H. Matsushita and Y. Nishio, "Network-Structured Particle Swarm Optimizer with Small-World Topology," in *Proc. of Int. Symposium on Nonlinear Theory and its Applications*, pp. 372–375, 2009.

[9] H. Matsushita, Y. Nishio and T. Saito, "Particle Swarm Optimization with Novel Concept of Complex Network," in *Proc. of Int. Symposium on Nonlinear Theory and its Applications*, pp. 197–200, Sep. 2010.

[10] H. Matsushita, Y. Nishio and T. Saito, "Behavior of Independent-Minded Particle Swarm Optimization," in *Proc. of RISP International Workshop on Nonlinear Circuits and Signal Processing*, pp. 103–106, Mar. 2011.

[11] H. Matsushita, Y. Nishio and T. Saito, "Application of Independent-Minded Particle Swarm Optimization to Parameter Search in Switched Dynamical Systems," in *Proc. of Int. Symposium on Nonlinear Theory and its Applications*, pp. 631–635, Sep. 2011.