Particle Swarm Optimization Based on Information Diffusion and Clonal Selection*

[1] Intelligent Multimedia Technology Lab, Department of Computer Science, Xiamen University, Xiamen, Fujian 3610005, China
catlet.lyp@gmail.com, szlig@xmu.edu.cn, QJiang@xmu.edu.cn
[2] Department of Mathematics, Jimei University, Xiamen, Fujian 361021, China
sgzx@jmu.edu.cn
[3] Department of Computer Science, Fuzhou University, Fuzhou, Fujian 350001, China

Abstract. A novel PSO algorithm called InformPSO is introduced in this paper. The premature convergence problem is a deficiency of PSOs. First, we analyze the causes of premature convergence for conventional PSO. Second, the principles of information diffusion and clonal selection are incorporated into the proposed PSO algorithm to achieve a better diversity and break away from local optima. Finally, when compared with several other PSO variants, it yields better performance on optimization of unimodal and multimodal benchmark functions.

1 Introduction

Particle swarm optimization is one of the evolutionary computation techniques based on swarm intelligence. In PSO, each solution is a point in the search space and may be regarded as a particle. The particle could find a global optimum through its own efforts and social cooperation with the other particles around it. Each particle has a fitness value and a velocity. The particles fly through the problem space by learning from the best experiences of all the particles. Therefore, the particles have a tendency to fly towards better search area over the course of search process.

The velocity and position updates of the i^{th} particle are as follows:

$$V_i(t+1) = w \cdot V_i(t) + c1 \cdot r1 \cdot (pBest_i - X_i) + c2 \cdot r2 \cdot (gBest - X_i) \tag{1}$$

$$X_i(t+1) = X_i(t) + V_i(t+1) \tag{2}$$

where X_i is the position of the i^{th} particle, V_i presents its velocity, $pBest_i$ is the best previous position yielding the best fitness value for it. $gBest$ is the best position discovered by the whole population and w is the inertia weight used to balance between the global and local search abilities. $c1$ and $c2$ are the acceleration constants, which

* This paper is supported by the National Natural Science Foundation (10471083) and the Natural Science Fund, Science & Technology Project of Fujian Province (A0310009, A0510023, 2001J005, Z0511008), the 985 Innovation Project on Information Technique of Xiamen University (2004-2007), Academician Fund of Xiamen University, China.

T.-D. Wang et al. (Eds.): SEAL 2006, LNCS 4247, pp. 521 – 528, 2006.

represent the weighting of stochastic acceleration terms that pull each particle towards *pbest* and *gbest* positions. $r1$ and $r2$ are two random functions in the range [0, 1].

The PSO algorithm is simple in concept, easy to implement and computationally efficient. Since its introduction in 1995 [1], PSO has attracted a lot of attention. Many researchers have worked on improving its performance in various ways. Some researchers investigated the influence of parameters in the PSO to improve its performance. A new inertia weight parameter is incorporated into the original PSO algorithms by Shi [2]. Another parameter called constriction coefficient is introduced to ensure the convergence of the PSO [3]. In [4], Ratnaweera et al. introduced to PSO the time varying acceleration coefficients in addition to the time varying inertia weight.

Many researchers have worked on improving PSO's performance by designing different types of topologies. Kennedy [5] claimed that PSO with a small neighborhood might perform better on complex problems, vice versa. Kennedy [6] tested PSOs with neighborhoods of regular shape. In [7], a dynamic neighborhood concept for their multi-objective PSO is proposed. FDR-PSO [8] with near neighbor interactions selects one particle with a higher fitness value to be used in the velocity updating equation.

Some researchers investigated hybridization by combining PSO with other evolutionary to improve the standard PSO's performance. Evolutionary operators like selection, crossover and mutation have been applied to PSO in [9]. In [10], each of the PSO, genetic algorithm and hill-climbing search algorithm was applied to a different subgroup and an individual can dynamically be assigned to a subgroup considering its recent search progress. In [11], CPSO employed cooperative behavior to significantly improve the performance of the original PSO algorithm by splitting the solution variables into a smaller number of variables in the search space.

The paper is organized as follows. Section2 analyses causes of premature convergence of traditional PSO algorithm and proposes an improved PSO algorithm. Results of experimental evaluation are given in Section 3, which contains the description of benchmark continuous optimization problems used for comparison of algorithms, the experimental setting for each algorithm, and discussions about the results. Section 4 gives conclusions and future work.

2 PSO Based on Information Diffusion and Clonal Selection

2.1 Premature Convergence

Though there are numerous versions of PSO, premature convergence when solving multimodal problems is still the main deficiency of the PSO. In the original PSO, each particle learns from its *pBest* and *gBest* simultaneously. Restrict the same social cognition aspect to all particles in the swarm appears to be somewhat an arbitrary decision. Furthermore, each particle obtains the same information from the *gBest* with others even if a particle is far from the *gBest*. In such situations, particles may be fleetly attracted and easily trapped into a local optimum if the *gBest* is in a complex search environment with numerous local solutions. Another cause of premature convergence of PSO is that the *pBest* and *gBest* have no contributions to the *gBest* from the velocity update equation. The current best particle in the original PSO always flies in its direction of previous velocity, which makes it easy to trap into a local optimum and unable to break away from it.

2.2 PSO Based on Information Diffusion and Clonal Selection (InformPSO)

In fact, information diffusion among biological particles is a time process. Particles, close to the current best particle (*gBest*), change the direction and rate of velocities fleetly towards it, while particles, far from it, move more slowly towards it. On the assumption that information is diffused among particles in a short time, information received by particles close to the *gBest* is more than that received by those far from it. Therefore, an information function , related to membership degrees with respect to its "surrounding", is incorporated into the PSO to adjust the variable "social cognition" aspect of particles.

In this improved version of PSO, the velocity update is expressed as follows:

$$V_i(t+1) = w \cdot V_i(t) + c1 \cdot r1 \cdot (pBest_i - X_i) + F\{\mu(d_i)\} \cdot c2 \cdot r2 \cdot (gBest - X_i) \quad (3)$$

where, $F\{\mu(d_i)\}$ is an information diffusion function, $\mu(d_i)$ represents the membership degree of i^{th} particle with respect to the "surrounding" of the *gBest*, d_i is the distance between particle i and the *gBest*. Here, the distance is measured by their position difference. By inspecting the expression in (3), we understand that particles perform variable-wise velocity update to the *gBest*. This operation improves the local search ability of PSO, increases the particles' diversity and enables the swarm to overcome premature convergence problem.

In order to pull the *gBest* to another direction if it is trapped in local optima, we use clonal selection operation on it. In multimodal problems, the *gBest* is often a local optimum, which may give other particles wrong information and lead to bad results. In our algorithm, we use a new method for the *gBest* to move out of local optima. First, the *gBest* is clonald [13] into a sub-swarm, then this sub-swarm mutates into a new one with different fitness values according to Cauchy distribution, finally the one with the highest fitness value is chosen as the *gBest* for velocity update of next generation. As a result, the *gBest* is improved in a local region by clonal selection operation, which enables the PSO algorithm effectively to break away from local optima.

3 Experimental Results

3.1 Benchmark Functions

In the experiments, nine different D dimensional benchmark functions [8] [14] [15] with different properties are chosen to test InformPSO's performance. The equations are listed below:

Table 1. Nine benchmark functions

Name	Function	Search Range	*x**	*f(x*)*
Sphere	$f_1 = \sum^{D} x_i^2$	[-100, 100]	0	[0,0,…0]
Hyper-ellipsoid	$f_2 = \sum_{i=1}^{D} i \cdot x_i^2$	[-5.12, 5.12]	0	[0,0,…0]

Table 1. (*continued*)

Sum of different powers	$f_3=\sum_{i=1}^{D}\lvert x_i\rvert^{i+1}$	[-1, 1]	0	[1,1,…1]
Rotated hyper-ellipsoid	$f_4=\sum_{i=1}^{D}\left[\sum_{j=1}^{i}x_j\right]^2$	[-65, 65]	0	[0,0,…0]
Rosenbrock	$f_5=\sum_{i=1}^{D}[100\cdot(x_{i+1}-x_i^2)^2+(x_i-1)^2)]$	[-2.048, 2.048]	0	[1,1,…1]
Griewank	$f_6=\frac{1}{4000}\sum_{i=1}^{D}x_i^2-\prod_{i=1}^{n}\cos(\frac{x_i}{\sqrt{i}})+1$	[-600, 600]	0	[0,0,…0]
Ackley	$f_7=20+e-20\exp(-0.2\sqrt{\frac{1}{D}\sum_{i=1}^{D}x_i^2})-\exp[\frac{1}{D}\sum_{i=1}^{D}\cos(2\pi x_i)]$	[-32.768, 32.768]	0	[0,0,…0]
Rastrigin	$f_8=\sum_{i=1}^{D}[x_i^2-10\cdot\cos(2\pi x_i)+10]$	[-5.12, 5.12]	0	[0,0,…0]
Weierstrass	$f_9=\sum_{i=1}^{D}(\sum_{k=0}^{k_{\max}}[a^k\cdot\cos(2\pi b^k(x_i+0.5))])-D$ $\sum_{k=0}^{k_{\max}}[a^k\cdot\cos(2\pi b^k\cdot 0.5)]$ $a=0.5, b=3, k_{\max}=20$	[-0.5, 0.5]	0	[0,0,…0]

3.2 Parameters Setting

To optimize these test functions, the error goal is set at 1e-40 and *w* is reducing with increasing generations from 0.9 to 0.4. *c1* and *c2* are both set at 2. Particles' initial positions are restricted by the search range and their velocities are restricted by V_{max}, which is equal to the search range. The number of generations, for which each algorithm is run, is set at *Max_Gen*. Except these common parameters used in PSOs, there

Table 2. The same parameters setting used for InformPSO, PSO_w with that used for traditional PSO, FDR_PSO [8]. *Initial Range*, variable range in biased initial particles; V_{max}, the max velocity; *Size*, the number of particles; *Max_Gen*, the max generation; *Dim*, the number of dimensions of functions.

Function	*Initial Range*	V_{max}	*Max_Gen*	*Size*	*Dim*
f1	[-5.12 ,5.12]	10	1000	10	20
f2	[-5.12, 5.12]	10	1000	10	20
f3	[-1, 1]	2	1000	10	10
f4	[-65.536, 65.536]	110	1000	10	10
f5	[-2.048, 2.048]	4	1500	10	2
f6	[-600, 600]	600	1000	10	10

Table 3. The same parameters setting used for InformPSO and PSO_w on four multimodal functions with that used for PSO_cf_local, UPSO, PSO_H, DMS_PSO [15] except for the parameter, *Max_Gen*

Function	*Initial Range*	V_{max}	*Max_Gen*	*Size*	*Dim*
f6	[-600, 600]	600	2000	30	30
f7	[-32.768, 32.768]	64	2000	30	30
f8	[-5.12, 5.12]	10	2000	30	30
f9	[-0.5, 0.5]	1	2000	30	10

is an additional parameter in InformPSO that needs to be specified. It is sub-swarm's population size, *m*. Suppose not to know if the function to be optimized is unimodal or multimodal, *m* is set at 10 for all functions.

3.3 Comparison with Other PSOs

In this part, we tested the same nine benchmark test functions using PSO_w. Parameters are the same setting with parameters setting for InformPSO in Table 2 and Table 3. Other interesting variations of the PSO algorithm (described below) have recently been proposed by researchers. Although we have not implemented all these algorithms, we conducted comparison with them using the results reported in the publications cited below:

- The original PSO [1].
- The modified PSO with inertia weight (PSO_w) [2].
- Local Version of PSO with constriction factors (PSO_cf_local) [7].
- Unified Particle Swarm Optimization (UPSO) [16].
- Fitness-distance-ratio based particle swarm optimization (FDR_PSO) [8].
- Cooperative PSO (CPSO_H) [11].
- Dynamic multi-swarm PSO (DMS_PSO) [15].
- Our improved PSO (InformPSO).

Figure1 presents the results of InformPSO and PSO_w on the first six optimization functions introduced in the previous section. The two algorithms were continuously performed for 30 trials on each function. The best fitness values of each generation have been plotted in graphs.

From Figure1 and graphs displayed in the literature [8], we see that InformPSO surpasses the three PSOs (PSO_w, traditional PSO, FDR_PSO) on each of the six functions. InformPSO has a significantly better global convergence ability. It achieves a sub-optima solution within 200 iterations for the first four unimodal functions. For Rosenbrock's and Griewank's functions, it gets global minima on most of trials. In each case, we find that the other three algorithms perform well in initial iterations, but particles easily reach the same fitness, consequently move into a local optimum. Furthermore, they fail to make further progress in later iterations, especially in multimodal problems. This does not happen in InformPSO as shown in all the graphs above, where the best fitness continues to differ for many iterations. InformPSO is able to move out of local optima in later iterations even being trapped in it. This effect was most marked for the last graph in Figure 1.

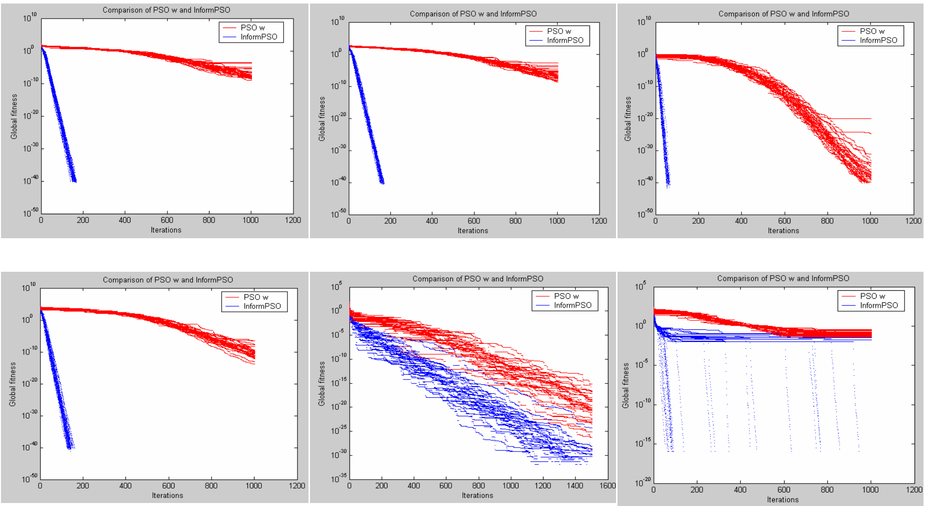

Fig. 1. InformPSO vs. PSO_w on f1-f6 functions

Table 4. The best and average results achieved on the first six test functions using traditional PSO and FDR_PSO [8], PSO_w and InformPSO

Algorithm Function	Best (Average) Fitness Values Achieved					
	Trad_PSO	FDR_PSO	PSO_w		InformPSO	
f1	0.0156	2.2415e-006	1.2102e-10	5.9724e-006	3.9843e-041	7.2610e-041
f2	2.1546e-007	1.8740e-015	1.7493e-009	8.0364e-005	2.3428e-041	6.9662e-041
f3	2.3626e-011	9.3621e-034	5.1684e-041	2.8907e-022	1.2685e-042	4.0353e-041
f4	0.0038	3.7622e-007	1.401e-014	1.9369e-008	2.8450e-041	6.6157e-041
f5	5.3273e-008	4.0697e-012	1.9722e-029	2.5544e-017	0	1.7027e-026
f6	1.3217e-008	1.1842e-016	0.0418	0.1152	0	8.2867e-003

Table 4 also shows that InformPSO yields better results for the six test functions than the other three PSOs. On average, InformPSO achieves the best and average fitness values in each case. It is able to converge to global optima on unimodal problems. It can find global optima or sub-optima for Rosenbrock's function and multimodal Griewank's function. As an example in point, it attains to the global minimum of Rosenbrock's function for 20 out of 30 trials and that of Griewank' function for 25 out of 30 trials.

Figure2 gives the results of InformPSO and PSO_w on four multimodal benchmark functions. The two algorithms were performed for 20 trials on each multimodal function. The best fitness values of each generation have been plotted in graphs.

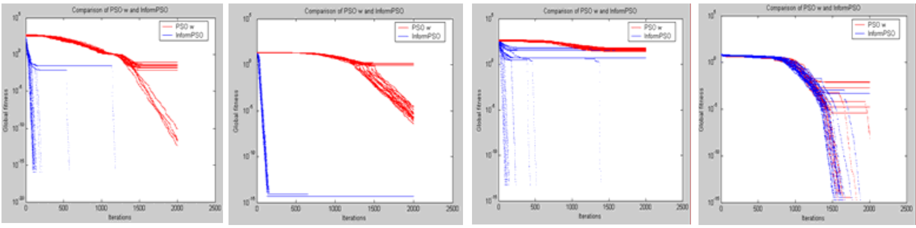

Fig. 2. InformPSO vs. PSO_w on the four multimodal functions

From graphs above, we observe that InformPSO yields better results for the four multimodal functions than PSO_w. Our proposed PSO algorithm rapidly finds global minima for three out of four multimodal functions except for Ackley's function. On multimodal functions, PSO_w rapidly loses the population diversity, and easily converge to a local optimum. And it is unable to improve the best fitness in later iterations. The population diversity of InformPSO results from its use of an information diffusion function in velocity update. The clonal selection operation contributes the best fitness to differing for many iterations. Thus, InformPSO is much less likely than the three PSO_w to get stuck in a local optimum and more effectively breaks away from a local optimum if being trapped in it. But our algorithm only attains a local solution to Ackley's function. PSO_w needs much more iterations to reach the same local solution. It seems that the two PSOs are unable to find the global optimum region for Ackley's function.

Table 5. The best and average results achieved by different PSOs [16]

Function / Algorithm	Best (Average) Fitness Values Achieved			
	f6	f7	f8	f9
PSO_w	4.308e-013 2.262e-002	7.268e-007 3.700e-001	26.824 43.828	0 1.291e-002
PSO_cf_local	4.971e-002	9.763e-008	9.769	1.812e-001
UPSO	3.453e-002	3.379e-009	14.231	2.226
CPSO_H	1.527e-001	1.715e+003	21.392	4.208
DMSPSO	2.338e-002	4.062e-009	3.277	0
InformPSO	0 0	4.441e-015 4.441e-015	0 7.661	0 1.806e-004

From the results, we can observe that among the six PSO algorithms, InformPSO performs the best results for Griewank's (f6) and Ackley's (f7) multimodal functions. Though when compared with DMSPSO, InformPSO achieves worse results for Rastrigin's (f8) and Weierstrass's (f9) function on average, it reaches the global minimum for 15 out of 20 trials on Rastrigin's function and for 19 out of 20 trials on Weierstrass's function. However, on Ackley's function, InformPSO and PSO_w fail to arrive in the global minimum region. These comparisons suggest that InformPSO surpasses many of the recent improvements of the PSO algorithm.

4 Conclusions

A novel PSO algorithm called InformPSO and one of its applications are introduced and discussed in this paper. In order to improve the local search ability and achieve a better diversity, information diffusion function is given to InformPSO. Particles perform variable-wise velocity update to the current best particle. In order to break away from local optima, clonal selection is incorporated into it. This new PSO algorithm gives better performance on unimodal and on complex multimodal problems when compared with other PSO variants.

References

[1] RC Eberhart, J Kennedy, "A new optimizer using particle swarm theory", *P. 6th on Micromachine and Human Science,* Japan, pp. 39-43, 1995.

[2] Y Shi, RC Eberhart, "A modified particle swarm optimizer", *CEC*, pp. 69-73, 1998.

[3] M Clerc, J Kennedy, "The particle swarm-explosion, stability, and convergence in a multidimensional complex space", *TEC*, Vol. 6, pp. 58-73, 2002.

[4] A Ratnaweera, S Halgamuge, "Self-organizing hierarchical particle swarm optimizer with time varying accelerating coefficients", *TEC*, Vol. 8, pp. 240 - 255, 2004.

[5] J Kennedy, "Small worlds and mega-minds: effects of neighborhood topology on particle swarm performance", *CEC*, pp. 1931-1938, 1999.

[6] J Kennedy, R Mendes, "Population structure and particle swarm performance", CEC'02, USA.

[7] X Hu, RC Eberhart, "Multiobjective optimization using dynamic neighborhood particle swarm optimization", CEC'02, pp. 1677-1681.

[8] T Peram, K Veeramachaneni, "Fitness-distance-ratio based particle swarm optimization'', *P. IEEE Swarm Intelligence Symp.,* USA, pp. 174-181, 2003.

[9] M Lovbjerg, TK Rasmussen, "Hybrid particle swarm optimizer with breeding and subpopulations", *P. Genetic Evol. Comput. Conj (GECCO)*, 2001.

[10] T Krink, M Lovbjerg, "The life cycle model: combining particle swarm optimization, genetic algorithms and hill Climbers", *P. Parallel Problem Solving from Nature VII*, pp. 621-630, 2002.

[11] F Bergh, AP Engelbrecht, "A cooperative approach to particle swarm optimization", *TEC*, Vol. 8, pp. 225 - 239, 2004.

[12] Huang Chongfu, "Principle of information diffusion", *Fuzzy Sets and Systems*, Vol. 91, pp. 69-90, 1997.

[13] FM Burnet, *The Clonal Selection Theory of Acquired Immunity*, Cambridge University Press, 1959.

[14] JJ Liang, AK Qin, "Particle Swarm Optimization Algorithms with Novel Learning Strategies", *SMC2004*, Netherlands, 2004.

[15] JJ Liang, PN Suganthan, "Dynamic Multi-Swarm Particle Swarm Optimizer", *Proc. of IEEE Swarm Intelligence Symp.*, pp. 124-129, 2005.

[16] KE Parsopoulos, MN Vrahatis, "UPSO- A Unified Particle Swarm Optimization Scheme", *LNCS*, pp. 868-873, 2004.