Incorporating Pheromone Courtship Mode into Swarm Intelligence with Convergence Analysis

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Abstract: In this paper, we incorporate pheromone courtship mode of biology to improve particle swarm optimizer. The particle swarm optimization technique has ever since turned out to be a competitor in the field of numerical optimization. A particle swarm optimization consists of a number of individuals refining their knowledge of the given search space. Particle swarm optimizations are inspired by particles moving around in the search space. The individuals in a particle swarm optimization thus have a position, a velocity and are denoted particles. The particle swarm optimization refines its search by attracting the particles to positions with good solutions. A new approach to particle motion in swarm optimization is developed. The living beings will release pheromone while seeking a spouse, use to attract the opposite sex to near. We tried to incorporate this kind of mode to solve the optimization problems. Preliminary simulation results show that the proposed method can solve the optimization problem with satistactory accuracy. Convergence analysis is investigated in this paper.

Key-Words: Pheromone, Pheromone Courtship Mode, Biology, Particle Swarm Optimization.

1 Introduction

In the nature, many living thing unfold many inconceivable social behaviors and the high wisdom, for example ant's groups, migratory bird's moving and looking for food, the fish group in order to evade the group class effect which preying on produces and so on. These behavior simple individuals compose the groups, which certainly do not have the leader and the central management, only depend on the simple rule between individual and the environment, and interacting with other individuals, only by observing the behavior of these simple individual which often let the person be unable to imagine, and look like simple the set of the simple region behavior, which actually can show Swarm Intelligence that cannot be forecast.

In the argument of community wisdom, the important point doesn't emphasis on studying about the complex structure of composition individual, and think that the complex system and the wisdom behavior by the individual interaction can appear to conform to the behavior of the system demand and the ability to strain the environment change. The comparison with traditional artificial wisdom method and central management system, the ability with the self-organization is the biggest community wisdom characteristic, besides using existing methods to urge the system, the second part is to "Explore" and "Exploit" the power of new methods, and then the system will have the elasticity to adapt to circumstances or environment, the system has tenacity and doesn't lead to stop all the system because of a small partial defeat.

Therefore the key point about community wisdom research is how to design the suitable interaction rules between the individuals, to let the system show the suitable and conforms to the demand integrity results. Marco proposed the Ant Colony Optimization in 1992[1]. Reynolds proposed the Cultural Algorithms in 1994[2] and so on, and the research about the Particle Swarm Optimization in this paper[3][4] all belong the methods of the community wisdom concept.

Though have so many studies about to promote performance in PSO research. There are probably in inertia weight, constriction factors and tracking dynamic system. And most research focus on inertia weight.

2 Particle Swarm Optimization

The particle swarm optimizer is a population based algorithm that was invented by Kennedy and Eberhart (1995)[4], which was inspired by the social behavior of animals such as fish schooling and bird flocking. Similar to other population-based algorithms, such as evolutionary algorithms, PSO can solve a variety of difficult optimization problems but has shown a faster convergence rate than other evolutionary algorithms on some problems. Another advantage of PSO is that it has very few parameters to adjust, which makes it particularly easy to implement.

Angeline (1998)[5] pointed out that although PSO may outperform other evolutionary algorithms in the early iterations, its performance may not be competitive as the number of generations is increased. Recently, several investigations have been undertaken to improve the performance of standard PSO (SPSO). Løbjerg et al. (2001)[6] presented a hybrid PSO model with breeding and subpopulations. Kennedy and Mendes (2002)[7] investigated the impacts of population structures to the search performance of SPSO. Other investigations on improving PSO's performance were undertaken using cluster analysis[8] and fuzzy adaptive inertia weight[9]. There is no information sharing among individuals except that P_g broadcasts the information to the other individuals. Therefore, the population may lose diversity and is more likely to confine the search around local minima if committed too early in the search to the global best found so far.

The SPSO model is based on the following two factors (Kennedy and Eberhart, 1995)[4]:

The autobiographical memory, which remembers the best previous position of each individual (P_i) in the swarm;

The publicized knowledge, which is the best solution (P_g) found currently by the population.

2.1 PSO Algorithm

PSO was originally developed by Eberhart and Kennedy in 1995 [10], and was inspired by the social behavior of a flock of birds. In the PSO algorithm, the birds in a flock are symbolically represented as particles. These particles can be considered as simple agents "flying" through a problem space. A particle's location in the multi-dimensional problem space represents one solution for the problem. When a particle moves to a new location, a different problem solution is generated. This solution is evaluated by a fitness function that provides a quantitative value of the solution's utility.

The velocity and direction of each particle moving along each dimension of the problem space will be altered with each generation of movement. In combination, the particle's personal experience, P_{id} and its neighbors' experience, P_{gd} influence the movement of each particle through a problem space. The random values rand1 and rand2 are used for the sake of completeness, that is, to make sure that particles explore a wide search space before converging around the optimal solution. The values of c1 and c2 control the weight balance of P_{id} and P_{gd} in deciding the particle's next movement velocity. At every generation, the particle's new location is computed by adding the particle's current velocity, Vid, to its location, Xid. Mathematically, given a multi-dimensional problem space, the ith particle changes its velocity and location according to the following Equations [1][2]:

$$Vid_{new} = w \times Vid_{old} + c_1 \times rand_1 \times \left(P_{id} - Xid\right) + c_2 \times rand_2 \times \left(P_{gd} - Xid\right) \tag{1}$$

$$Xid_{new} = Xid_{old} + Vid_{new} \tag{2}$$

where w denotes the inertia weight factor; P_{id} is the location of the particle that experiences the best fitness value; P_{gd} is the location of the particles that experience a global best fitness value; c1 and c2 are constants and are known as acceleration coefficients; d denotes the dimension of the problem space; rand1, rand2 are random values in the range of (0, 1).

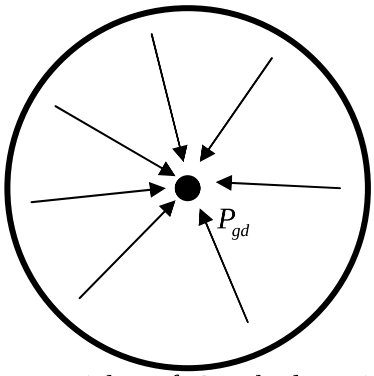

Fig. 1. The particles of Standard particle swarm optimizer are effect by P_{gd} .

3 Pheromone Courtship Mode

In this paper, we tried to merge pheromone courtship mode of biology for Particle Swarm Optimization (PSO) . In the biological evolution ways, it's often utilize the way to looking for the outstanding spouse to propagate the next generation with better gene. Making use of the distributing of pheromone, it can be more effective to attract opposite sex. Thus, the probability succeeding of breeding will increase.

In brief, we tried to merge pheromone courtship mode of biology for PSO. According to the above narrations, we replace the part of P_i of PSO with the effect of neighboring insects. And we replace the part

of P_g of PSO with the effect of insects with higher pheromone thickness. According to the value of its position, determine the influence power of the insect correctly. The pattern by the simulation of the insect is affected by pheromone, and then to decided the position of the advancing. Try to use this kind of method, We attempt use this way to cause it not to be able to fall into the situation of the local best solution. And uses this way to increase its performance.
The algorithm is as follows:

1. Get the random values for set $\{NUM\}$ in the range of function, and the quantity of $\{NUM\}$ is Num_all.
2. Take the $\{NUM\}$ into fitness function, and arrange according to its value size.
3. Arrangement according to fitness function value, and part as two sets. The quantity of strong set $\{M\}$ is Num_M. The quantity of set $\{F\}$ is Num_F. And Num_all = Num_M + Num_F.
   $\{M\}=\{M_1,M_2,M_3,...,M_{Num\_M}\}$ and $\{F\}=\{F_1,F_2,F_3,...,F_{Num\_F}\}$
   $f(M_1)>f(M_2)>...>f(M_{Num\_M})>f(F_1)>f(F_2)...>f(F_{Num\_F})$
4. Get the random value for Set $\{NUM\}$ in the range.
5. Get the F_{i_new} from taking the Vid_{i_new} into equation(4).
6. Reload $\{NUM\}=\{M_1,M_2,M_3,...,M_{Num\_M},F_{1\_new},F_{2\_new},F_{3\_new},...,F_{Num\_F\_new}\}$
7. Repeat step 2 to 6, until the value convergence reaches the constant.

Equations (3):

$$Vid_{i\_new}=\sum_{j=1}^{p}\eta_j(M_j-F_i)+\left[\rho_1(M_x-F_i)+\rho_2(M_y-F_i)+\rho_3(M_z-F_i)\right] \tag{3}$$

Equations (4):

$$F_{i\_new}=F_i+Vid_{i\_new} \tag{4}$$

In equation(3), p means the quantity of strong set power effect. Here we used 3, its means there are three particle of strong set. M_x,M_y,M_z means three most close strong set effect. And ρ_1,ρ_2,ρ_3 is the parameter of M_x,M_y,M_z.

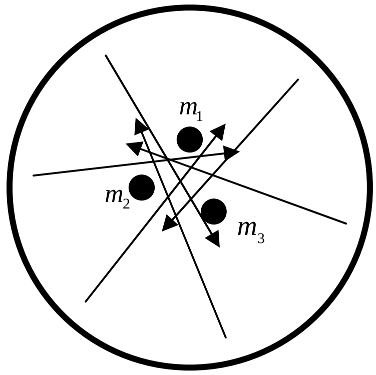

Fig. 2. The particles within Pheromone Courtship Mode are effect by the stronger insects.

4 Simulation Results

In our experimental studies, a set of 4 benchmark functions was employed to evaluate the algorithm in comparison with others.

Sphere model:

$$f_1(x)=\sum_{i=1}^{30}x_i^2$$

Schwefel's Problem 1.2:

$$f_2(x)=\sum_{i=1}^{30}\left(\sum_{j=1}^{i}x_j\right)^2$$

Generalized Rosenbrock's function:

$$f_3(x)=\sum_{i=1}^{29}\left(100\left(x_{i+1}-x_i^2\right)^2+\left(x_i-1\right)\right)^2$$

Generalized Rastrigin's function:

$$f_4(x)=\sum_{i=1}^{30}\left(x_i^2-10\cos\left(2\pi x_i\right)+10\right)^2$$

To evaluate the performance of the proposed algorithm, standard PSO were used for comparisons. The experiment of this part has been finished. Preliminary simulation results show that the proposed method can provide greater efficiency and satisfactory accuracy. For uni-modal functions (function f_1 – f_3), the convergence rates are more important than the final results of optimization as there are other methods such as gradient-based search methods that are designed specially to optimize uni-modal functions[11]. From Figs. 3–6, it can be show that algorithms has a fast convergence rate. Functions f_4 are multi-modal functions that are very difficult to optimize, since the number of local minima increases exponentially as the function dimension increases[12][13].

4.1 Convergence Analysis

From the Table 1, we can find the better factors. When the $(\eta_1,\eta_2,\eta_3) = (0.6, 0.4, 0.2)$ and the other factors $(\rho_1,\rho_2,\rho_3) = (0.3, 0.2, 0.2)$, there are better astringency with the function. Even though the third factors (η_3, ρ_3) have not the powerful effect. But if it has the right set, it's helpful to the convergence.

Table 1 astringency analysis with f_1

(η_1,η_2,η_3)	(ρ_1,ρ_2,ρ_3)	Global-Best
(1, 1, 0)	(0, 0, 0)	33.585
(1, 0.8, 0)	(0, 0, 0)	54.438
…	…	…
(0.6, 0.4, 0)	(0.3, 0.2, 0)	7.18E-21
(0.6, 0.4, 0.2)	(0.3, 0.2, 0.2)	4.59E-25
(0.6, 0.3, 0.2)	(0.3, 0.2, 0.2)	1.49E-16
(0.6, 0.5, 0.2)	(0.3, 0.2, 0.2)	1.15E-15
(0.6, 0.4, 0.1)	(0.3, 0.2, 0.2)	6.05E-18
(0.6, 0.4, 0.3)	(0.3, 0.2, 0.2)	5.65E-15
(0.6, 0.4, 0.2)	(0.3, 0.3, 0.2)	9.37E-10
(0.6, 0.4, 0.2)	(0.3, 0.2, 0.1)	2.88E-23
(0.6, 0.4, 0.2)	(0.4, 0.2, 0.2)	9.02E-18

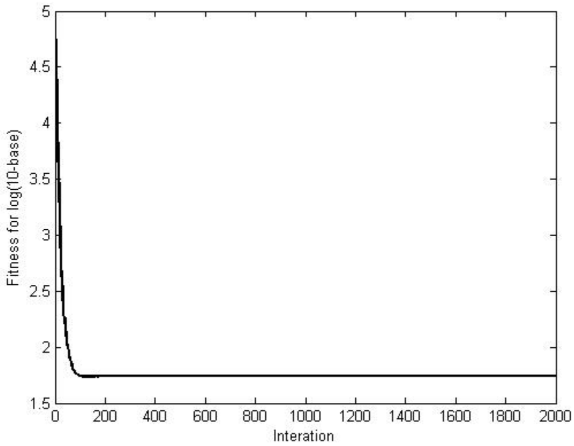

Fig 4: The convergence of the proposed algorithm when parameters $(\eta_1,\eta_2,\eta_3,\rho_1,\rho_2,\rho_3)$ =(1 0.8 0, 0 0 0)

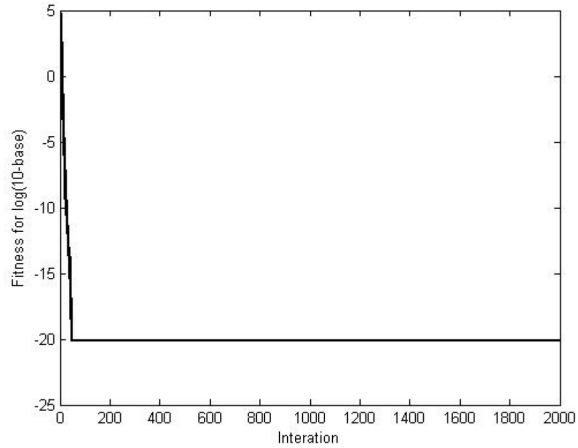

Fig 5: The convergence of the proposed algorithm when parameters $(\eta_1,\eta_2,\eta_3,\rho_1,\rho_2,\rho_3)$ =(0.6 0.4 0, 0.3 0.2 0)

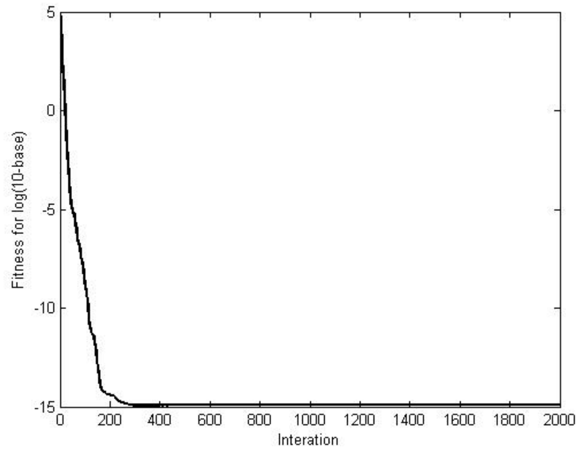

Fig 6: The convergence of the proposed algorithm when parameters $(\eta_1,\eta_2,\eta_3,\rho_1,\rho_2,\rho_3)$ =(0.6 0.5 0.2, 0.3 0.2 0.2)

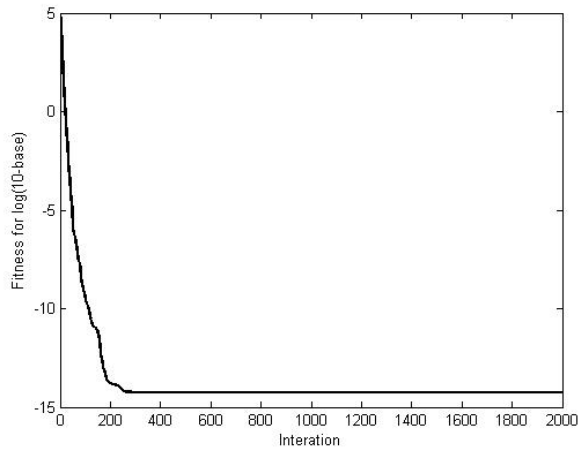

Fig 7: The convergence of the proposed algorithm when parameters $(\eta_1,\eta_2,\eta_3,\rho_1,\rho_2,\rho_3)$ =(0.6 0.4 0.3, 0.3 0.2 0.2)

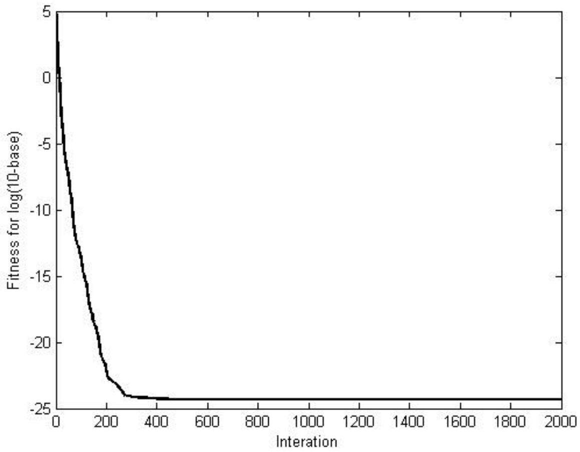

Fig 8: The convergence of the proposed algorithm when parameters $(\eta_1, \eta_2, \eta_3, \rho_1, \rho_2, \rho_3)$ =(0.6 0.4 0.2, 0.3 0.2 0.2)

4.2 Performance Analysis

Table 2 Basic characters of the test functions

Function	n	Feasible solution space	$f_{\min}$
f_1	30	$[-100,100]^n$	0
f_2	30	$[-100,100]^n$	0
f_3	30	$[-30,30]^n$	0
f_4	30	$[-5.12,5.12]^n$	0

In this paper, we try these four test functions. The table 2 show the characteristics. 'n' is the number of variables. There are the Performance analysis figure. (figure 3-6)

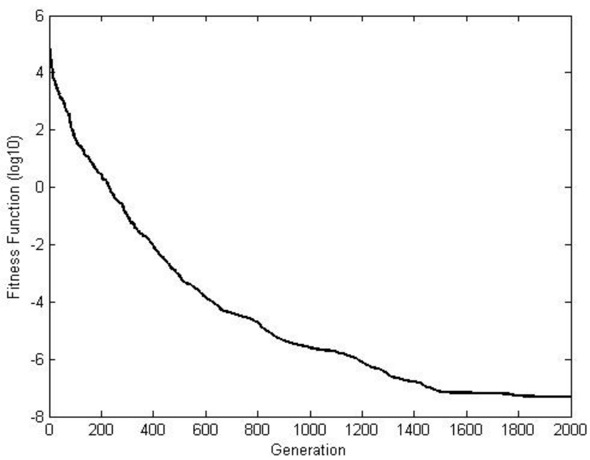

Fig. 3. f_1, Sphere model.

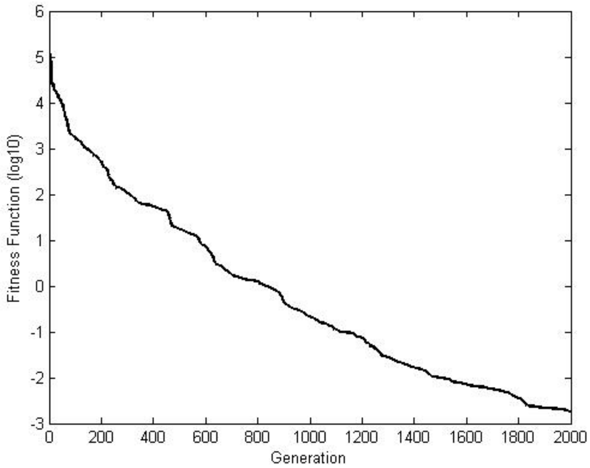

Fig. 4. f_2, Schwefel's Problem 1.2.

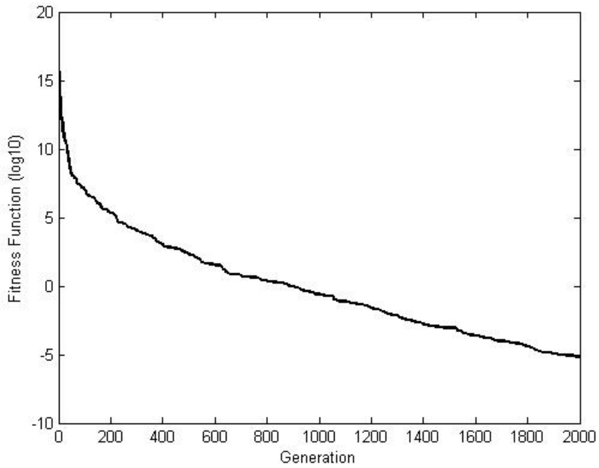

Fig. 5. f_3, Generalized Rosenbrock's function.

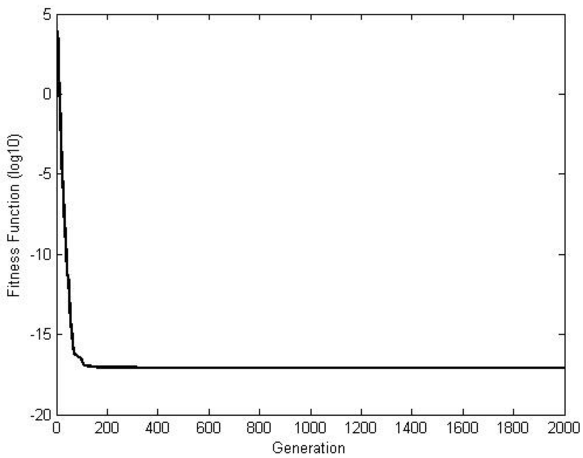

Fig. 6. f_4, Generalized Rastrigin's function.

5 Conclusion

In this paper, a new PSO based on Pheromone Courtship Mode has been presented on the traditional PSO. By introducing Pheromone Courtship Mode, information can be transferred among individuals that will help individuals to avoid misjudging information and becoming trapped by poor local minima. The only coefficient introduced into the standard PSO is the Pheromone Courtship Mode. A generic value of η and ρ was selected by experiments. A set of 4 benchmark functions has been used to test PSO based on Pheromone Courtship Mode. Among the experimental, three functions were uni-modal and one was multi-modal. For the multi-modal benchmark functions, PSO based on Pheromone Courtship Mode found better results than those generated by the standard PSO. For most of the uni-modal functions, of which the convergence rate is more important than the final results, our PSO based on Pheromone Courtship Mode performed accuracy and convergence rate. The results indicated that the benchmark functions, PSO based on Pheromone Courtship Mode performed significantly better than the traditional PSO.

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