

# Study and Improvement on Particle Swarm Algorithm

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**Abstract**—An improved particle swarm optimizer (IPSO) with artificial immune algorithm (AIA) is proposed based on basic particle swarm optimization (BPSO). IPSO which is divided into two phases during the evolutionary process is different from BPSO. AIA remaining the diversity of population is applied in the first phase. Sub-population is formed by the optimum values sorted near the top from the first phase. Some sub-population evaluate at the same time to improve the performance of local convergence and get the global optimum value. Most Benchmark function get good result with IPSO which ability of optimization is better than BPSO.

**Index Terms**—IPSO, AIA, two phases, optimization

## I. INTRODUCTION

Particle Swarm Optimization (PSO) was proposed based on bird foraging behavior by Dr Eberhart and Kennedy In 1995. PSO which attracts extensive attention from academics in recent years is a highly efficient search algorithms due to the simply concept, easy implementation, fast convergence and less parameter settings[1].

PSO is a heuristic algorithm for global optimization. Dr Eberhart and Kennedy learned from animal foraging groups which adjust the next search for direction and size according to the individual in the optimal position in the groups and the optimum position of its own history when the entire group to search for a target. The model of groups foraging behavior was designed to solve function optimization problems through the method of experiments and progressive correction step by step. PSO often sinks into the local convergence in the optimization process for the complex function optimization, so it lacks

of access to the global optimum value.

In order to improve convergence properties of the algorithm, there have been various improvements based on different algorithms. Some scholars study on the parameters selection and optimization. Shi and Eberhart first introduced inertia weight in the velocity update equations to extend the search space and improve the ability to explore new areas[2]. Clerc presents a PSO with shrinkage factor algorithm similar to the maximum speed limit which can improve the convergence of the algorithm[3]. Monson improved location formula updating the particle location using Kalman filtering, which effectively reducing the number of iterations[4].

In swarm intelligence optimization algorithms, the important reason of prematurity is that the difference between individuals is smaller and the algorithms cannot jump out of the local area after a period of running time. Diversity is an important factor affecting the convergence performance of algorithms. Zhibin Liu and Ling Zhang proposed the algorithm which unified the ant colony optimization and PSO effectively[5]. Liang and Suganthan give the PSO algorithm with multiple groups which divided the algorithm into two stages. Each stage uses different search strategies [6]. The algorithm improved the diversity of particles, achieve good balance between exploration and development and speed up the pace of global optimization. PSO algorithm is also integrated with other ones to learn each other by some scholars. An improved discrete PSO algorithm which introduced live operators to ensure dynamic characteristics of population size was given by Sadri Javad based on genetic thought[7]. Kao yi-Tung and others have come up with a GA-PSO method which is combined with heuristic optimization technology, genetic

algorithm and PSO algorithm for solving complex practical problems[8]. Shengli Song and Yong Gan proposed improved algorithm in which the centroid of particle swarm is introduced in PSO model[9]. The above algorithms improve the accuracy of PSO algorithm to a certain extent, but some improved ones' computational complexity boost and the implementation of the algorithm efficiency is impacted.

This paper inspired by the diversity of antibody in the biological immune system proposed improved immune PSO algorithm. The algorithm combines artificial immune algorithm good global search capabilities and PSO algorithm.

## II. PARTICLE SWARM OPTIMIZATION ALGORITHM

### A. Principle of Algorithm

PSO algorithm simulates the bird foraging behavior which is to achieve the goals through collective collaboration and competition among birds. In PSO, Each alternative solution is called a "particle" and many particles are in coexistence and cooperation for the optimal value similar to birds in search of food. At first PSO algorithm produces initial population, that is, randomly initiates a group of particles in the feasible solution space. Each particle is a feasible solution to optimization problems and fitness value is determined by the objective function. Each particle moves in the solution space and its direction and distance are determined by the speed. Particles usually move following the optimal one and get optimal solutions by iterative search. In each generation, particles trace two extremes; a  $P_{best}$  is the optimal solution for the particle itself so far and another for the whole population so far to find the optimal solution for  $G_{best}$ .

Mathematical description in PSO is as following: each single solution in the search space is a "bird" which can be called "particle". There are  $n$  particles forming a population in a  $d$ -dimensional search space. Each particle represent a possible solution and have a position vector  $x_i$ , a velocity vector  $v_i$ , and the best personal position  $p_i$  encountered so far by the particle. PSO is initialized with a group of random particles and then searches for optima by updating generations. In each generation, each particle moves in the direction of its own personal best position  $p_i$ , as well as in the direction of the global best position  $p_g$  discovered so far by any of the particles in the population. As a result,  $p_i$  and  $p_g$  can be used to adjust their own velocities and positions. This means that if a particle discovers a promising new solution, all other particles will move closer to it. At each generation, the velocity and the position of a particle  $i$  is updated using Eq 1 and 2:

$$v_{id}^{k+1} = \omega v_{id}^k + c_1 r_1 (p_{id} - z_{id}^k) + c_2 r_2 (p_{gd} - z_{id}^k) \quad (1)$$

$$z_{id}^{k+1} = z_{id}^k + v_{id}^{k+1} \quad (2)$$

Where  $w$  is the inertia weight and typically setup to vary linearly from 0.9 to near 0.4 during the course of an iteration run;  $c_1$  and  $c_2$  are acceleration coefficients;  $r_1 \sim$

$U(0, 1)$  and  $r_2 \sim U(0, 1)$  are uniformly distributed random numbers in the range (0,1)[10]. The velocity  $v_i$  is limited to the range  $[v_{min}, v_{max}]$ . Updating velocity in this way enables the particle  $i$  to search around its individual best position  $p_i$ , and the global best position  $p_g$ . The position  $z_i$  is limited to the range  $[z_{min}, z_{max}]$ .

Iterative termination conditions according to the specific problem are maximum number of iterations or the optimum position searched meeting the minimum adaptation threshold.

### B. Algorithm steps

The steps of PSO are as following:

- 1 In accordance with the initialization process, random position and velocity of particles are set initially.
- 2 Calculate the fitness value of each particle.
- 3 The fitness of each particle should be compare with its own personal best position  $P_{best}$  and if the value is better than  $P_{best}$ , the new position would be the position as the current  $P_{best}$ .
- 4 The fitness of each particle should be compare with global best position  $G_{best}$  and if the value is better than  $G_{best}$ , the new position would be the position as the current  $G_{best}$ .
- 5 Velocity and position of particles should be adjusted by formula 1 and 2.
- 6 If it cannot meet the end conditions, jump to 2.

## III. IMPROVED PARTICLE SWARM OPTIMIZATION

The efficiency and accuracy of algorithm are affected because the ability of space exploration and development cannot be used effectively by just one algorithm in the study of evolutionary algorithm. Two or more algorithms with different optimization mechanism are integrated into one algorithm which can maximize the characteristics of various algorithms.

The diversity of particle population is an important factor affecting the convergence of the PSO algorithm, so diversity of population can effectively improve the ability of global convergence. Continuous tracking to the  $G_{best}$  makes particles more similar to each other during the running of the PSO. PSO has fast convergence rates, but is easy to local optimization. Particles lose diversity gradually in the solving process. Remain the diversity and not reduce the homoplasy are important for improving the performance of the global convergence in PSO. IPso combining PSO and AIA is proposed in this paper.

### A. Artificial Immune Algorithm

AIA is Bionic algorithm proposed simulating intelligent behavior of biological immune system, and it is a combination of deterministic and stochastic choice and stochastic heuristic search algorithm with surveying and mining capabilities[11]. In AIA optimization problems problem to be optimized corresponds to the Antigen in immune response, feasible solution corresponding antibody, quality of solution corresponding affinity of antibodies and Antigen. That evolution chains of Biological immune response are

abstracted to the evolutionary optimization process in mathematics formed intelligent optimization algorithm.

The algorithm includes the following major modules:

1 Antigen recognition and initial antibody initialization: appropriate antibody coding rules are defined according to the characteristics of optimization problem and the initial population is produced by the prior knowledge of the problem under the rules.

2 Antibody evaluations: the quality of antibody is evaluated according to the evaluation criteria which is decided by the affinity and density of antibody. Excellent antibodies evaluated would implement evolutionary operation and poor antibodies would be updated.

3 Clone selections: all kinds of immune operations in biological immune response are simulated by the immune selection, clone, variation, inhibition and refreshment. Rules and methods of evolution are formed based on the principles of biological immune system to realize the optimal search of all kinds of problems.

Artificial immune algorithm inspired by Immunology is adaptive intelligent system, simulating biological immune system and principle to resolve complex problems and retaining some characteristics of the immune system. AIA is a optimization algorithm with global searching ability[12], ensuring feasible solutions in full range and global convergence properties. AIA draw on the diversity maintain mechanisms of biological immune system, calculating antibody density and inhibiting ones with high density, which keeps a good diversity of antibody population[13]. AIA with very strong adaptability and robustness depends less on problem and initial solution.

**B. Related Definitions**

Definition 1 Affinity is combination strength of immune cells and antigen, similar to the fitness in PSO. For the different optimization problems, the function of fitness should be defined by understanding according to the substance and features of the problem. Definition is given as follows:

$$\text{affinity}(xi) = \frac{1}{f + 1} \tag{3}$$

f in the formula is the value of function to be optimized. For the minimum value of the function, antigen is the optimal solution meeting the constraints of objective function to be optimized and antibody is candidate solutions xi of function. When f is smaller, affinity is higher and much closer to the antibodies and antigens.

Definition 2 Antibody density Antibody density represents diversity of population. High density means abundant similar individuals existing in the population which is not good at global optimization. The individual of high density should be inhibited to ensure the diversity of individuals[14].

The definition of antibody density is as follows:

$$\text{den}(abi) = \frac{1}{N} \sum_{j=0}^{N-1} \text{aff}(ab_i, ab_j) \tag{4}$$

N is the size of population size, abi is the ith antibody, aff(abi,abj) is the affinity of antibody i and antibody j. The premise for evaluation of antibody density is the

definition of antibody-antibody affinity. Antibody-antibody affinity can often be calculated from the continental distance between antibodies for the real number coding algorithm.

$$\text{aff}(ab_i, ab_j) = \sqrt{\sum_{k=0}^{L-1} (ab_{i,k} - ab_{j,k})^2} \tag{5}$$

abik and abjk are k-d of antibody i and antibody j and L is the total dimensions of antibody coding.

Definition 3 Incentive Antibody incentive is determined by the affinity and density of the antibody. The antibody with high affinity and low density could get higher incentive generally. Incentive can be calculated by the evaluation result of affinity and density.

$$\text{sim}(ab_i) = a \times \text{aff}(ab_i) - (1-a) \times \text{den}(ab_i) \tag{6}$$

a is a parameter determined by the actual situation.

Definition 4 Variation Variation operation on the antibody is to realize affinity mutation and the further research. Variation is an important operation to produce new potential antibody. The operation of real number coding algorithm makes the antibody deviated from the original position and fallen into an another individual neighborhood location by a small disturbance.

$$T_m(ab_{i,j,m}) = ab_{i,j,m} + (\text{rand}() - 0.5) * \delta(7)$$

δ is a range of neighborhood and rand() is a random function in (0,1).

**C. Description of Algorithm**

Many scholars combine these two algorithms to improve optimization capabilities according to the features of AIA's good global searching ability and PSO's local ability. That AIA is applied to the PSO is a method adopted by the most scholars. When PSO trapped into the local convergence, the operation of clone and variation would be executed to jump out the local convergence.

The approach in this paper is the evolutionary process is divided into two phases. AIA is adopted in the first phase to improve the diversity of population with good global searching ability. PSO is adopted in the second phase in which m antibody sorted by the affinity near the top are selected to build m sub-populations. Local search is executed in each sub-population to get global optimization solution finally. The steps are described in figure 1.

1 According to antigen recognition to understand the problem to be optimized and define the function of fitness.

2 Generate an initial population randomly abi, i=0,1,...,N-1, N is the size of population.

3 if meet the pre-determined number of iterations, jump to 8.

4 Estimate every feasible solution in population.

5 Calculate antibody density.

6 Do immune treatment including immune selection, clone, variation and inhibition

Immune selection: Activate antibody which is selected by the calculating result of affinity and density of

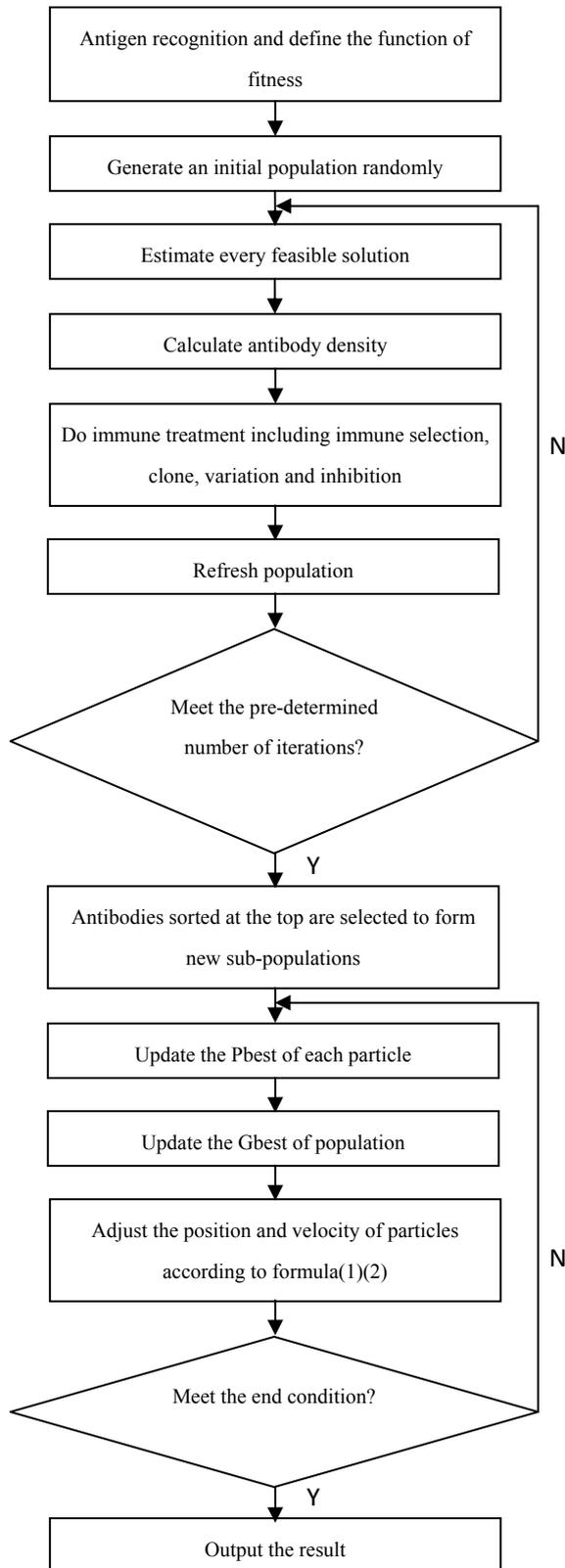


Figure 1 Steps of improved PSO

antibody in population.

Clone: Copy the activated antibody and get some copies.

Variation: Perform variation operation on the copies to

change affinity.

Clone and inhibition: Inhibit low affinity antibodies and retain the high affinity ones according to the result of variation.

7 Refresh population: new antibodies randomly generated that replace the antibody with low affinity form a new iteration population. Jump to 3.

8 M antibodies sorted at the top are selected and each forms a new sub-population with the rest of N-M antibodies.

9 The fitness of each particle should be compare with

its own personal best position pbest and if the value is better than pbest, the new position would be the position as the current pbest.

10 The fitness of each particle should be compare with global best position Gbest and if the value is better than Gbest, the new position would be the position as the current Gbest.

11 Velocity and position of particles should be adjusted by formula 1 and 2.

12 If it cannot meet the end conditions, jump to 9.

The end conditions are maximum number of generations or optimal solution searched so far meeting the intended accuracy requirements. The best solution in M sub-population is the optimal solution.

#### IV. PERFORMANCE ANALYSIS AND EVALUATION OF IPSO

##### A. Parameter Settings and Benchmark Function Selection

In order to balance the local and global search during the evolutionary process, a linearly varying inertia weight (w) is over the course of generations and value is in the range [0.4,0.9]. When w changes from big to small, the search space of particle changes from a wide space to a small space gradually. A large number of experiments proved that if  $\omega$  linear decrease in the iterations of the algorithm, the performance of convergence would be improved greatly. c1 and c2 are learning factors usually  $c1=c2=2$

Four typical Benchmark function are selected to be test function. F1 and F2 is a unimodal function which can test optimal accuracy of algorithm and explore the performance efficiency. F3 and F4 is multimodal with large numbers of local minimizers, generally more difficult to find the optimal value. At the time of simulation, BPSO and IPSO with AIA are tested respectively. Parameter settings of two algorithms are the same and the number of iterations is 500. Four functions are run on its own for 50 times and are compared by the average value. Four functions are set up for the 10-dimension, for the range of F1, F2, F3 [-100,100], F4 [-600,600] and the target minimum value is 0.

##### B. Performance Comparison of Algorithms

The test on 4 Benchmark function are executed 50 times respectively using two different algorithms. The average, minimum, and standard deviation are shown in table 1. When Benchmark functions are optimized by BPSO, the result of other three function especially F3: Rastrigin is poor but F1: Sphere. IPSO algorithm is able

to reach the position very near the global location and standard deviation is low which prove its stability.

Figure 2 to Figure 5 show the comparison of performance of two optimization algorithm for four

functions. The optimal accuracy of BPSO is not great, especially for multimodal functions, but the accuracy of IPSO is quite great generally.

TABLE 1  
COMPARISON OF RESULTS

	BPSO			IPSO		
	Average	minimum	Standard Deviation	Average	minimum	Standard Deviation
f1	1.9550E-01	0	3.1271E-01	0	0	0
f2	4.3131E-01	0	9.9222E-01	2.1624E-11	0	3.2516E-11
f3	4.2768E+01	1.0831E+1	2.0977E+01	2.6542E-12	0	2.3645E-11
f4	2.9770E-01	4.4293E-02	2.0277E-01	4.3968E-12	0	3.2123E-12

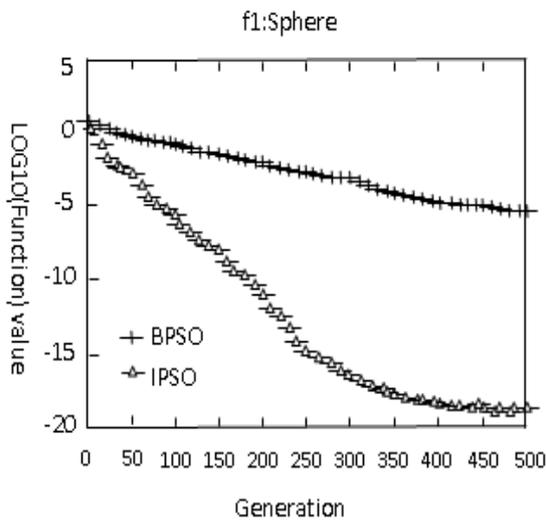


Figure2 Simulation results of f1

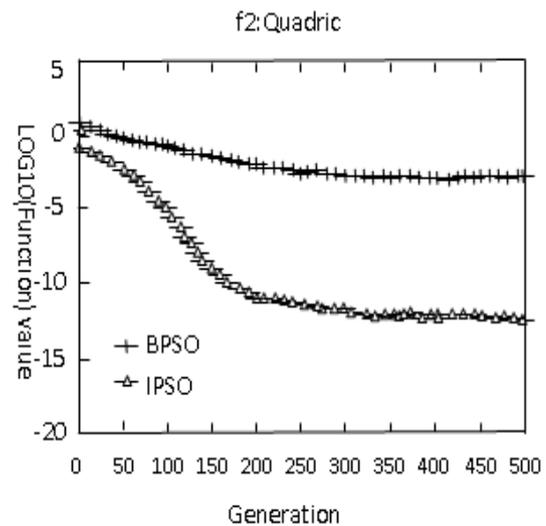


Figure3 Simulation results of f2

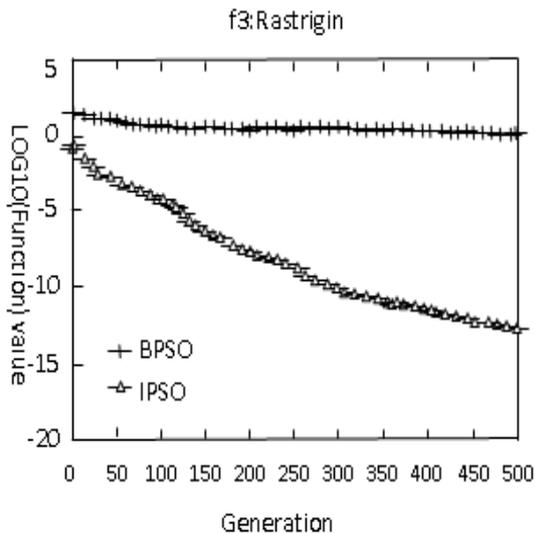


Figure4 Simulation results of f3

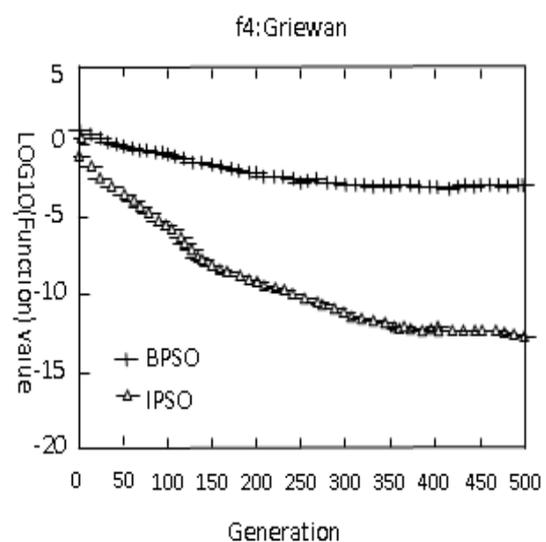


Figure5 Simulation results of f4

V. CONCLUSIONS

BPSO is a randomized global optimization mechanism. In each generation, each particle moves in the direction of its own personal best position  $P_{best}$ , as well as in the direction of the global best position  $G_{best}$  discovered so far by any of the particles in the population. The

population of particles tends to cluster together and decrease the diversity of population after a certain number of iterations. BPSO is easy to be in the local convergence. AIA is applied in the BPSO in this paper and IPSO is proposed. Through simulation the ability of optimization of IPSO is significantly better than the one of BPSO, especially in the case of multiple local

extremes. That the entire process is divided into two phase is the core thought of IPSO. AIA is adopted in the first phase to ensure the diversity of population. BPSO is adopted in the second phase in which m antibody sorted by the affinity near the top are selected to build m sub-populations. Local search is executed in each sub-population to get global optimization solution finally. BPSO is adopted in the second phase in which m antibody sorted by the affinity near the top are selected to build m sub-populations. Local search is executed in each sub-population to get global optimization solution finally which balances global and local search and improves the success rates of optimization.

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