

Study On an Improved Co-Evolutionary Particle Swarm Optimizer and Its Application

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Abstract

In order to overcome the drawbacks of falling into local extremum and lower optimization precision of standard particle swarm optimization (PSO) algorithm, multi-population strategy, adaptive dynamic adjustment strategy and co-evolution mode are introduced into the standard PSO algorithm in order to propose an improved co-evolutionary PSO(MPACEPSO) algorithm based on multi-strategy evolution mode and multi-population co-evolutionary mechanism. In the evolutionary process of MPACEPSO algorithm, the multi-population strategy is used to divide the population into several sub-populations, which use different co-evolutionary model to evolve. These sub-populations are influenced and promoted each other in order to realize the exchange of information and co-evolution among the sub-populations, improve the convergence speed and search precision of MPACEPSO algorithm, and effectively suppress the appearance of the local optimum. The adaptive dynamic adjustment strategy of inertia weight is used to keep the diversity of population, reduce the probability of falling into the local extremum. Finally, the ZDT functions are selected to test the optimization performance of proposed MPACEPSO algorithm. The experimental results show that the proposed MPACEPSO algorithm has faster convergence speed, stronger global search ability, higher solving precision and better dynamic optimization performance. The experimental result analysis shows that the proposed MPACEPSO algorithm is insensitive to parameters and easy to be used in solving the complex optimization problems.

Keywords: *Particle swarm optimization; co-evolution; adaptive dynamic adjustment; multi-population; optimization performance*

1. Introduction

Swarm intelligence (SI) algorithm is a new optimization technology, which has been concerned by researchers from the mid-1990s [1]. The conception of SI originated from observation and research the biological swarm behavior of ants, geese, fish and so on. It is an intelligent method by describing intelligent phenomenon inspiring in the nature and biological swarm [2-3]. Particle swarm optimization (PSO) algorithm [4] is a typical swarm intelligence algorithm, which derived from simulating foraging behavior of birds and fish swarm. Because the PSO algorithm has simple concept, quick convergence speed, less parameters, easy realizing and strong global optimization ability, it is widely applied in solving these optimization problems of function optimization, neural network training, combined optimization, digital circuit optimization and so on.

The PSO algorithm has shown its good performance in many optimization problems, but for some complex problems, it exist two main deficiencies [5]: (1) The PSO algorithm likes other stochastic optimization algorithm, in order to jump out local extremum and expand the scope of the search, the considerable amount of calculation is used in searching for poor fitness value. (2) In the whole iterative process, the particles fly to direction of the current found global optimal value position, even if the global optimal value is just local extreme point. The speed of particle will soon reduce to zero and not fly,

this will cause that the particle converges to local extremum point. For these existing deficiencies, the scholars have proposed a lot of improved PSO algorithms. Feng [6] proposed, a powerful evolutionary particle swarm optimization (PSO) learning algorithm to automatically tune the centers and spreads of each radial basis function, and the connection weights. Ni *et al.* [7] proposed a general hybridized PSO with chaos for a fast infrared image segmentation method. General hybridized PSO with chaos is based on general PSO, and it makes use of adaptive balance searching strategy. When the evolution stops, simulated annealing algorithm is introduced to select the current global optimum to be chaotic optimized for the sake of enhancing local searching ability and overcoming premature convergence. Pan *et al.* [8] proposed a new strategy on parameter selection of PSO algorithm, which did not depend on expert experience. It transformed the parameter-selection problem into functional optimization problem by creating a function of the PSO property parameters. Li *et al.* [9] proposed a hybrid (named MOPSO) algorithm based on particle swarm optimization (PSO) for a multi-objective permutation flow shop scheduling problem. The MOPSO algorithm not only applies the parallel evolution mechanism of PSO characterized by individual improvement, population cooperation, and competition to effectively perform exploration but also utilizes several adaptive local search methods to perform exploitation. Yu *et al.* [10] proposed an improved particle swarm optimization (PSO) and discrete PSO (DPSO) with an enhancement operation by using a self-adaptive evolution strategies (ES) for joint optimization of three-layer feed forward artificial neural network (ANN) structure and parameters (weights and bias). Hota *et al.* [11] proposed an improved PSO (IPSO) technique that deals with an inequality constraint treatment mechanism called as dynamic search-space squeezing strategy to accelerate the optimization process and simultaneously. Lee and Ko [12] proposed a nonlinear time-varying evolution particle swarm optimization (NTVE-PSO) algorithm, which is a dynamically adaptive optimization approach using the nonlinear time-varying evolutionary functions for adjusting inertia and acceleration coefficients. Qu *et al.* [13] proposed an improved method named Particle Swarm Optimization (PSO) clustering algorithm based on cooperative evolution with multi-populations. It adopts cooperative evolutionary strategy with multi-populations to change the mode of traditional searching optimum solutions. It searches the local optimum and updates the whole best position (gBest) and local best position (pBest) ceaselessly. Ko *et al.* [14] proposed a novel evolutionary computation algorithm, nonlinear time-varying evolution particle swarm optimization (NTVEPSO). In the NTVEPSO method, the nonlinear time-varying evolution functions are determined by using matrix experiments with an orthogonal array. Zhao *et al.* [15] proposed an improved particle swarm optimization with decline disturbance index (DDPSO) to deal with the problems of the slow convergence rate and the tendency to trap into premature. Theoretical analysis, which is based on stochastic processes, proves that the trajectory of particle is a Markov processes and DDPSO algorithm converges to the global optimal solution with mean square merit. Wang *et al.* [16] proposed an improved self-adaptive particle swarm optimization algorithm (ISAPSO) to solve hydrothermal scheduling (HS) problem. To overcome the premature convergence of particle swarm optimization (PSO), the evolution direction of each particle is redirected dynamically by adjusting the two sensitive parameters of PSO in the evolution process. Hong [17] proposed a new encoding method based on maximum entropy principle and fuzzy technique (MEPFPSO) for representing real number parameters in particle swarm optimization (PSO). In the method, the value of a parameter is represented by a group of cluster centers and their degree membership functions which are belonged to their centers. Li and Deng [18] proposed an electoral cooperative particle swarm optimization (ECPSO) based on several sub-swarms to solving the permutation flow shop scheduling problem (PFSSP). In the proposed algorithm, several strategies are employed to avoid falling into local optimum, improve the diversity and achieve better solution. Lin *et al.* [19] proposed two random learning factor particle swarm

optimizations with chaos. In the algorithms, the ergodicity of chaos is introduced respectively at early and late stage of evolution. Nanda and Panda [20] proposed an automatic clustering algorithm MOIMPSO (Multi-objective Immunized Particle Swarm Optimization) based on a recently developed hybrid evolutionary algorithm Immunized PSO. The proposed algorithm provides suitable Pareto optimal archive for unsupervised problems by automatically evolving the cluster centers and simultaneously optimizing two objective functions. Wang and Yan [21] proposed a global best harmony search algorithm with control parameters co-evolution based on particle swarm optimization (PSO-CE-GHS). In PSO-CE-GHS, two control parameters, *i.e.* harmony memory considering rate and pitch adjusting rate, are encoded to be a symbiotic individual of original individual (*i.e.* harmony vector). Harmony search operators are applied to evolve the original population. Wang *et al.* [22] proposed a novel variant of particle swarm optimization (PSO), named membrane optimization algorithm based on mutated particle swarm optimization (MO-MPSO). The MO-MPSO algorithm is an appropriate combination of membrane computing, evolution rules of PSO algorithms and a mutation operator. Zhao *et al.* [23] proposed a new improved hybrid PSO-based genetic algorithm (HPSO-GA) on the basis of parallel genetic algorithms (PGA). In this algorithm, chaos initialization, hybrid strategy and multi-subpopulation evolution based on improved adaptive crossover and mutation are adopted. Zeng *et al.* [24] proposed a novel particle swarm optimization (PSO) based on a non-homogeneous Markov chain and differential evolution (DE) for quantification analysis of the lateral flow immunoassay (LFIA), which represents the first attempt to estimate the concentration of target analyze based on the well-established state-space model. Dong *et al.* [25] proposed a particle swarm optimization sleep scheduling mechanism for use in wireless sensor networks based on sleep scheduling algorithm. The mechanism adopts the approach of density control and finds the redundant nodes based on the computation results of the network coverage.

2. Particle Swarm Optimization (PSO) Algorithm

The PSO algorithm is a population-based search algorithm based on the simulation of the social behavior of birds within a flock [4]. In PSO algorithm, individuals, referred to as particles, are “flown” through hyper dimensional search space. The particles’ positions within the search space are changed based on the social-psychological tendency of individuals in order to delete the success of other individuals. The changing of one particle within the swarm is influenced by the experience, or knowledge. The consequence of modeling for this social behavior is that the search is processed in order to return toward previously successful regions in the search space. Namely, the velocity(v) and position(x) of each particle will be changed by the particle best value (pB) and global best value (gB). The velocity and position updating of the particle is shown by the followed expression:

$$v_{ij}(t+1) = wv_{ij}(t) + c_1r_1(pB_{ij}(t) - x_{ij}(t)) + c_2r_2(gB_{ij}(t) - x_{ij}(t)) \quad (1)$$

$$x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1) \quad (2)$$

Where $v_{ij}(t+1)$, is velocity of particle i^{th} at iterations j^{th} , $x_{ij}(t+1)$, is position of particle i^{th} at iterations j^{th} . w is inertia weight to be employed to control the impact of the previous history of velocities. c_1 is the cognition learning factor, c_2 is the social learning factor, r_1 and r_2 are random numbers uniformly in $[0, 1]$, which denote remembrance ability for study. Generally, the value of each component in V can be clamped to the range $[-V_{max}, V_{max}]$ to control excessive roaming of particles outside the search space.

3. Multi-Strategy

3.1. The Adaptive Dynamic Adjustment Strategy of Inertia Weight

In general, in order to obtain better performance of PSO algorithm, the value of inertia weight w is more in the early search in order to ensure the search of population in the larger scope of search space for avoiding premature convergence. With the increase of the number of iteration, the value of inertia weight w is less in order to adjust the search of population in the smaller scope of search space for improving the convergence accuracy. The adjustment method of inertia weight in the PSO algorithm with linear decreasing weight is described:

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{T_{\max}} \times t \quad (3)$$

Where w_{\max} and w_{\min} are the maximum value and minimum value of inertia weight. t is the current number of iteration. T_{\max} is the maximum number of iteration. The actual search process of PSO is non-linear, the dynamic changes of operation of particles are complex, the PSO algorithm with linear decreasing weight can not reflect the actual optimization search process, the convergence speed and convergence precision are not satisfactory. At the same time, the optimal gradient of linear decreasing weight depends on the different solving problem, there is no existing universal the optimal gradient for all optimization problems. So an adaptive dynamic adjustment strategy of inertia weight is proposed in order to keep the diversity of population, reduce the probability of falling into the local extremum.

$$w = \begin{cases} w_{\min} + \frac{w_{\max} - w_{\min}}{T_{\max}} \times t & f < \frac{f_{avg}}{2} \\ w_{\min} + (w_{\max} - w_{\min}) \times \frac{\frac{f_{avg}}{2} - f_{\min}}{f - f_{\min}} & \frac{f_{avg}}{2} \leq f < f_{avg} \\ w_{\max} - \frac{w_{\max} - w_{\min}}{T_{\max}} \times t & f \geq f_{avg} \end{cases} \quad (4)$$

Where f is the current fitness value of the particle, f_{\min} is the global minimum fitness value of the particle. f_{avg} the global current average fitness value. The adaptive dynamic adjustment strategy of inertia weight will use the current information and historical information to the future updating speed, rely on different problems to make the corresponding adjustment in order to better reduce the probability of falling into local extremum.

3.2. Multi-Population Co-Evolutionary Mode

Coevolution is an evolutionary computation idea by imitating the evolution mechanism of the species in the nature ecosystem. Coevolution algorithm (CEA) is based on the collaborative evolution theory, it is a new class of evolution algorithm in recent years. The collaborative evolution theory recognizes the diversity of biology, emphasizes the dependency between the biology and the biology, between the biology and the environment in the evolutionary process. All populations with the coevolution are prompted influenced and restricted by each other in order to improve the local and global performance. The diversity can effectively improve the global convergence ability of the

PSO algorithm. Be inspired by the co-evolutionary algorithm, the coevolution algorithm of multi-population is used to realize the optimization by collaborative reaction among multiple populations. This algorithm emphasizes to implement the evolution of the entire system among the different independent species in order to eliminate the limitations of traditional single evolutionary algorithm. So multi-population co-evolutionary algorithm has become a research hotspot in solving practical dynamic optimization problems.

Multi-population co-evolutionary algorithm is to divide the population into several sub-populations for co-evolution. The co-evolutionary mode has two kinds of common models: the island model and neighborhood model. The two models directly divide the individuals of the population into several sub-populations. Each sub-population represents a subspace in the solution space, and is optimized and updated according to their respective search strategy. The searched better individual will be migrated among the different sub-populations, and regarded as shared information to guide the evolution in order to effectively improve the searching efficiency. And each sub-population cooperatively updates the speed and position of particles in order to take on strong global and local convergence ability in the running process of the PSO algorithm, ensure the strong spatial exploration and exploitation ability in the search process of particles, and accelerate the search speed of the population, improve the convergence precision, the accuracy and efficiency in the optimization process.

4. An Improved Co-Evolutionary Particle Swarm Optimizer

The proposed MPACEPSO algorithm divides the individuals into M sub-populations with same individuals, and each sub-population contains the number of particles

$n = \frac{N}{M}$ (N is the population size). Each sub-population shares the initial global optimal

$pbest$ of particle. Every interval S generations, the current $pbest_i (i = 1, 2, 3, \dots, M)$ in M sub-populations are compared in order to obtain the global best $pbest$ to be shared by each sub-population for speeding up the search. The model of an improved co-evolutionary particle swarm algorithm is shown in Figure1.

The steps of the improved co-evolutionary PSO (MPACEPSO) algorithm are described:

(1). Initialize

In proposed MPACEPSO algorithm, some parameters need be initialized. They are particle size N , the number of sub-population M , learning factor c_1 and c_2 , the maximum and minimum of inertia weight w_1 and w_2 , the number of maximum iteration T_{max} . The initial velocity and initial position of each particle in the population are randomly assigned under meeting the constraints of control variables.

(2). Compute the fitness value

Construct a fitness function according to solving complex optimization problem, then the fitness value of each particle is calculated. And the best fitness values and the corresponding positions of particle, sub-population and population are recorded.

(3). Divide sub-populations

The population is divided into M sub-populations with same particles. For each sub-population, the global best position of the i^{th} particle $gbest_i$ is equal to $gbest$.

(4). Calculate the new velocity and position of individual

The new velocity and position of individual are calculated according to the formula (1), and (2). And the new velocity and position of particle are limited the maximum and minimum values. At the same time, the historical best fitness value and historical best position of particle and sub-population are updated.

(5). Obtain the best *gbest*

Each sub-population is independently searched, and each particle in the sub-population generates a new particle according to its own evolutionary pattern. If the particle cannot update its own *pbest*, the other evolution model is used to replace the current evolution model. Every interval *S* generations, the current $pbest_i (i=1,2,3,\dots,M)$ in *M* sub-populations are compared in order to obtain the global best *gbest* to be shared by each sub-population for speeding up the search.

(6). The global historical best fitness value and position of population are updated.

(7). Determine whether the termination condition (the maximum number of iteration) is meet. If the termination condition is meet, go to (8). Otherwise, return (4).

(8). Stop to search, and output the obtained optimal position.

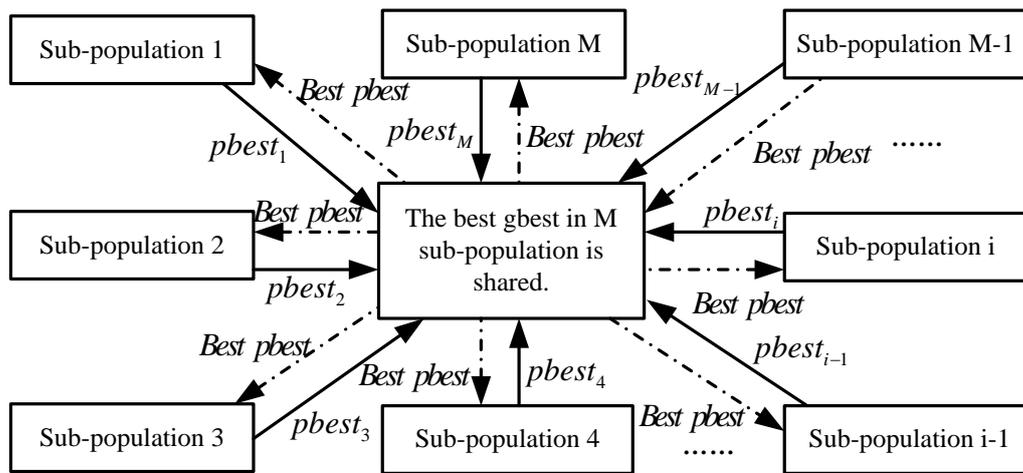


Figure1. The Model of MPACEPSO Algorithm

5. Numerical Experiments

In order to test the effectiveness of proposed MPACEPSO algorithm, some existing evolutionary multi-objective optimization methods (such as PSO algorithm, co-evolutionary particle swarm optimization (CEPSO) algorithm, multi-objective comprehensive learning PSO (MOCLPSO) algorithm) are selected to compare with the proposed MPACEPSO algorithm. And five ZDT functions are selected to evaluate the performance of these algorithms. The expressions of the five test functions are shown in Table1. The experiment environment is described: the Pentium IV, 2.20GHz, 2.0GB RAM, Windows 7 and Matlab 2012b. The experimental parameters are given: population size $N = 66$, the number of subpopulations $M = 3$, learning factor $c_1=1.5$ and $c_2=1.8$, the minimum and maximum of inertia weight $w_1=0.5$ and $w_2=1.0$, the minimum velocity $V_{max}=100$, the number of maximum iteration $T_{max}=500$. These algorithms are independently run 20.

Table 1. The Expressions of the Five Test Functions

| Function | Objective function (minimization) | Dimension | variable |
|----------|--------------------------------------|-----------|--------------------------------------|
| ZDT_1 | $f_1(x) = x_1$ | 10 | $x_i \in [0,1]$ $i = 1,2,\dots,n$ |
| | $f_2(x) = g(x)[1 - \sqrt{x_1/g(x)}]$ | | |

| | | | |
|---------|---|----|--|
| ZDT_2 | $g(x) = 9\left(\sum_{i=2}^n x_i\right)/(n-1) + 1$ $f_1(x) = x_1$ $f_2(x) = g(x)[1 - (x_1/g(x))^2]$ | 10 | $x_i \in [0,1]$ $i = 1, 2, \dots, n$ |
| ZDT_3 | $g(x) = 9\left(\sum_{i=2}^n x_i\right)/(n-1) + 1$ $f_1(x) = x_1$ $f_2(x) = g(x)[1 - \sqrt{x_1/g(x) - x_1/g(x)\sin(10\pi x_1)}]$ | 10 | $x_i \in [0,1]$ $i = 1, 2, \dots, n$ |
| ZDT_4 | $g(x) = 9\left(\sum_{i=2}^n x_i\right)/(n-1) + 1$ $f_1(x) = x_1$ $f_2(x) = g(x)[1 - \sqrt{x_1/g(x)}]$ $g(x) = \sum_{i=2}^n [x_i^2 - 10\cos(4\pi x_i) + 10(n-1) + 1]$ $f_1(x) = 1 - e^{(-4x_1) \times [\sin(6\pi x_1)]^6}$ | 10 | $x_1 \in [0,1]$ $x_i \in [-5,5]$ $i = 2, \dots, n$ |
| ZDT_6 | $f_2(x) = g(x)[1 - (f_1(x)/g(x))^2]$ $g(x) = 9\left[\left(\sum_{i=2}^n x_i\right)/(n-1)\right]^{1/4} + 1$ | 10 | $x_i \in [0,1]$ $i = 1, 2, \dots, n$ |

In given five standard test functions, the part of the decision variables of ZDT functions exist simple linear correlation. PS of ZDT functions are $0 \leq x_1 \leq 1, x_2 = x_3 = \dots = x_n$ except that PS of ZDT_3 is piecewise continuous.

In the experiment, an inverted generational distance (IGD) is used to evaluate the performance of MPACEPSO algorithm. Assume that P^* is a set of uniform sampling for the ideal PF of multi-objective optimization problem (MOP). P is to obtain a set of approximation solution of the ideal PF, the IGD index of solution set P is defined:

$$IGD(P^*, P) = \frac{\sum_{v \in P^*} d(v, P)}{|P^*|} \quad (5)$$

Where $d(v, P)$ is the nearest Euclidean distance between the distance and v population P , $|P^*|$ is a number of Pareto optimal solutions in the population P^* . In here, $|P^*| = 300$. The IGD index can comprehensively measure the convergence and diversity of obtained Pareto optimal solutions P by using multi-objective optimization algorithm. If the value of IGD is smaller, the solving performance of algorithm is better.

The IGD result has been shown in Table 2.

Table 2. The IGD Result for Four Algorithms

| Function | Index | PSO | CEPSO | MOCLPSO | MPACEPSO |
|----------|------------|----------|----------|----------|----------|
| ZDT_1 | Mean value | 3.04E-01 | 2.75E-02 | 8.43E-03 | 5.16E-03 |

| | | | | | |
|---------|------------|----------|----------|----------|----------|
| | Std. | 2.59E-01 | 1.52E-01 | 6.03E-02 | 4.86E-02 |
| ZDT_2 | Mean value | 2.23E-01 | 3.41E-02 | 6.68E-03 | 5.79E-03 |
| | Std. | 2.59E-01 | 8.36E-02 | 2.42E-02 | 3.54E-03 |
| ZDT_3 | Mean value | 1.52E-01 | 4.24E-02 | 1.21E-02 | 3.52E-03 |
| | Std. | 3.02E-01 | 6.53E-02 | 3.41E-03 | 2.59E-03 |
| ZDT_4 | Mean value | 2.04E-00 | 5.47E-01 | 3.73E-02 | 2.15E-02 |
| | Std. | 3.08E-00 | 4.06E-01 | 2.83E-02 | 2.69E-02 |
| ZDT_6 | Mean value | 4.32E-01 | 1.94E-02 | 5.52E-03 | 3.81E-03 |
| | Std. | 3.82E-01 | 8.31E-02 | 4.92E-02 | 6.35E-04 |

As can be seen from the Table2, for selected simple test functions of ZDT_1 , ZDT_2 and ZDT_3 , the CEPSO algorithm, MOCLPSO algorithm and MPACEPSO algorithm can find the Pareto optimal solutions, which converge to the ideal PF. The uniformity and comprehensiveness are better, and the difference of obtained results is not significant. But for selected simple test functions of ZDT_4 and ZDT_6 , PSO algorithm and CEPSO algorithm can not convergence to the ideal of PF, MOCLPSO algorithm and MPACEPSO algorithm can be a good convergence to the ideal of PF. And for ZDT_6 , the proposed MPACEPSO algorithm takes on better uniformity. In summary, the proposed MPACEPSO algorithm based on combining multi-population strategy, adaptive dynamic adjustment strategy and co-evolution mode can obtain the best solution by analyzing the experiment results. It takes on better optimization performance than the PSO algorithm, and the CEPSO algorithm, MOCLPSO algorithm in solving complex optimization problems. Especially for testing complex nonlinear correlation between decision variables, the proposed MPACEPSO algorithm takes on obvious advantage.

6. Conclusions

In this paper, an improved co-evolutionary PSO (MPACEPSO) algorithm based on multi-population strategy, adaptive dynamic adjustment strategy and co-evolution mechanism is proposed. In order to overcome the drawbacks of falling into local extremum and lower optimization precision of standard particle swarm optimization (PSO) algorithm, the multi-population strategy is used to divide the population into several sub-populations, which use different co-evolutionary model to evolve. These sub-populations are influenced and promoted each other in order to realize the exchange of information and co-evolution among the sub-populations, improve the convergence speed and search precision of MPACEPSO algorithm, and effectively suppress the appearance of the local optimum. The adaptive dynamic adjustment strategy of inertia weight is used to keep the diversity of population, reduce the probability of falling into the local extremum. The comparative study showed that the proposed MPACEPSO algorithm can obtain the solution sets that are highly competitive with respect to convergence, diversity, and distribution, for five ZDT functions. Due to no limitation on objectives, the proposed MPACEPSO algorithm can be extended to more objectives problems.

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