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A New MOPSO Based on Pairing Selection and Adaptive Strategy

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Abstract: In order to improve the performance of particle swarm optimization, aim at the poor convergence rate and the poor local optimum search capabilities, proposing an improved multi-objective particle swarm optimization. The algorithm is based on the information transmission mechanism between particle swarm, uses SPEA2 environmental selection and pair selection strategy in algorithm to make the population of particles quickly converge to Pareto optimal boundary and uses adaptive principle to change the calculation method of the speed weight to enhance the algorithm's global search capability. Through the simulation experiments of classic test functions and the application of robot path planning, the results show that the improved algorithms make the algorithm not only makes it easier to jump out of the local algorithm but also makes the convergence speed of algorithm and the convergence speed of particle populations have been greatly improved, also makes the robot path planning algorithm can more quickly find the optimal road king.

Keywords: Adaptive principle, environmental selection and pairing selection strategy, multi-objective particle swarm optimization.

1. INTRODUCTION

As a new optimization method, particle swarm algorithm is a computation technology based on intelligent community [1]. Compared with other evolutionary algorithms such as genetic algorithm (GA), the advantage of particle swarm optimization algorithm is as follows [2]: First, compared with evolutionary algorithm the particle swarm algorithm is simple easier to achieve; Second, the particle swarm optimization algorithm has profound biological background; Third, there is little parameter need to adjustment in the particle swarm algorithm.

Recently, Particle swarm algorithm is suitable for scientific research, and suitable for engineering application. Therefore, the particle swarm optimization studies have been carried out, especially with the obvious advantages of particle swarm optimization algorithm shown in single objective optimization problems, which promotes the academic improve the research efforts to PSO.

But because the study of particle swarm optimization algorithm is still at the initial stage, there are many problems worth studying. The following are a few particle swarm algorithm problem what worth to be concerned [1]:

Firstly, the basic theory of particle swarm optimization algorithm is not perfect, the work mechanism of PSO cannot give a good mathematical explanation, what also lack mathematical proof. Second, although the particle swarm optimization algorithm has improved, but because the era of progress and the development of society. At present, the improved particle swarm algorithm cannot meet the needs of real life. Third, the Application field of particle swarm algorithm needs to expand. Since the multi-objective particle swarm algorithm first used in multi-objective problem in 1999 [3], the multi-objective particle swarm algorithm has many problems need to be solved. such as, There is not a unified evaluation standard; Population particle is easy to fall into the local optimal; For the selection of The best individual historical value position and the global optimal value of the location of the population are full of randomness and so on. On this basis, a lot of different versions MOPSO are produced what can be roughly divided into six categories: Composite weighted MOPSO [4, 5]; the lexicographic MOPSO [6, 7]; MOPSO with sub populations [8, 9]; MOPSO based on Pareto method [10-16]; mixed MOPSO [17]; other MOPSO [18, 19];

In the study of these six multi-objective particle swarm, ultimately that is through a variety of methods to improve the performance of the algorithm [20] , So that the algorithm can achieve more in more application in many field. By reading the relevant literature, this paper presents a choice based on the environment, pairing selection strategy and adaptive principle to improved multi-objective particle swarm optimization. Through the simulation experiments of classic test function, the results show that the improved algorithm let the convergence speed of population particle and the search ability of the algorithm have been improved. Through the application of the improved algorithm in robot path planning, the results show that the improved algorithm can quickly find the optimal path what validate the feasibility and effectiveness of the improved algorithm and proved the improved algorithm has some practical value.

2. MULTI-OBJECTIVE OPTIMIZATION PROBLEM

2.1. Mathematical Description

Multi-objective optimization problems generally consist of $P=[s,p_1,p_2,....,p_n,e]$ decision vector and $\min\ f(P)=(f_1(P),f_2(P),...,f_n(P))$ objective vector, the model of multi-objective optimization problem is as follows [21, 22]:

$$\begin{aligned} \min\quad & F(x)=(f_1(x),f_2(x),...,f_m(x))^T \\ s.t.\quad & g_i \le 0, \qquad i=1,2,...,q \\ & h_j = 0, \qquad j=1,2,...,p \end{aligned} \tag{1}$$

Where, $x=(x_1,\cdots,x_n)\in X\subset R^n$ is decision vector with n-dimensional, X is decision space with m-dimensional, $f(x)$ is target vector with m-dimensional $g_i(x)\le 0$. Definition q inequality constraints, $h_j(x)=0$ Definition q inequality constraints.

Feasible solution: For $x\in X$, if x satisfies the constraint functions $g_i\le 0(i=1,2,\cdots,q)$ and $h_j=0(j=1,2,\cdots,p)$, Said x is a Feasible solution。

The feasible solution set: It is consist of all feasible solution in X, named as X_f, and $X_f\subseteq X$

Pareto dominate: A vector

$$\min F(x)=(f_1(x),f_2(x),f_3(x))$$

$$f_1(x)=\sum_{i=1}^{n-1}|\,p_ip_{i+1}\,|$$

$$f_2(x)=\frac{\sum_{i=1}^{n}(180-\theta_i)}{n}s$$

$$s=\sqrt{\sum_{i=1}^{n}\left(180-\theta_i-f_2(x)\right)^2}$$

$$f_3(x)=1/d$$

is said to dominate another vector P_i, denoted by P_{i+2}, if P_{i+1} and P_{i+2}, Where $f_{a,i}<f_{b,i}$.

Pareto optimal solution: A solution is called Pareto optimal solution (or non-dominated solution), only if the following conditions are met:

$$\neg\exists x\in X_f : x\succ x^* \tag{2}$$

Pareto optimal set: Pareto optimal set is a set of all the Pareto optimal solutions:

$$P^*\overset{\Delta}{=}\left\{x^*\,|\,\neg\exists x\in X_f : x\succ x^*\right\} \tag{3}$$

2.2. Evaluation Criteria

How to evaluate the performance of optimization algorithms has been a difficult multi-objective optimization studies, for this, Deb proposed a closer evaluation method [23]. This method is used to calculate the solution set to the reference set or the Pareto optimal solution set minimum distance approach to Measure the extent of algorithm approaching. The smaller of the distance, indicating that the higher approach of the solution set.

The method requires the use of reference sets P^* in convergence performance evaluation of a multi objective evolutionary algorithm. The reference set P^* is either the Pareto optimal solution set what is known, or the non dominated set the non dominated set union. That is $P^*=nondo\min ated(\mathrm{U}_{t=0}^{T}\mathrm{NDSet}^{(t)})$, where $\mathrm{NDSet}^{(t)}$ is the non-dominated set of t generation evolution $P^{(t)}(\mathrm{t}=0,1,\cdots,\mathrm{T})$. Because the Pareto optimal solution set of multi-objective problem is generally difficult to obtain, so the reference set P^* is usually the non dominated set the non dominated set union. The specific steps are as follows:

First, Calculation of the shortest distance from the non dominated individuals i to P^*. As the formula (4) is shown below:

$$Pd_i=\min_{j=1}^{|P^*|}\sqrt{\sum_{k=1}^{m}\left(\frac{f_k(\mathrm{i})-f_k(\mathrm{j})}{f_k^{\max}-f_k^{\min}}\right)^2} \tag{4}$$

In the formula (4), $f_k^{\max}$ and $f_k^{\min}$ are the maximum and minimum values of k target in reference set P^*, m is the number of sub-objective function.

Then, calculate the average value of a, As the formula (5) is shown below:

$$C(P^{(t)})=\sum_{i=1}^{NDSet^{(t)}} pd_i\,/\,|\,\mathrm{NDSet}^{(t)}\,| \tag{5}$$

In order to meet the $C(P^{(t)})\in[0,1]$ Do as the formula (6) for processing method is shown:

$$\bar{C}(P^{(t)})=C(P^{(t)})/C(P^{(0)}) \tag{6}$$

$C(P^{(t)})$ is a measure of the multi-objective problem solving set approach degree of value, The smaller the value, shows that the more tends for the solution set to Pareto optimal boundary. Conversely higher the value, the lower tends for the solution set to Pareto optimal boundary. $\bar{C}(P^{(t)})$ values between 0-1, When used to express the multi-objective algorithm convergence speed, The smaller the value, the faster the convergence shows that the solution set, and the greater its value, it indicates that the slower convergence of the solution set

This article will use the following two methods to verify the improved algorithm for enhancing the performance of the algorithm is valid:

The first evaluation criteria: Calculated the distance between the non dominated set of the new population particles after iteration and Pareto optimal boundary. What is used to evaluate the convergence speed of algorithm.

The second evaluation criteria: Calculated the distance between the new population of particles after iteration and Pareto optimal boundary.

3. PARTICLE SWARM OPTIMIZATION AND ITS IMPROVEMENT

The main innovation of this improved algorithm has two main aspects on one hand is to introduce environmental selection strategy and paired selection strategy of SPEA2 to multi-objective particle swarm algorithm; what can provide an evaluation criteria for the algorithm to reduce the large number of random choice on Individual optimal value and historical value of the global optimum population. On the other hand, introduce adaptive strategies to MOPSO, what can change the speed of the weight control methods. Specifically as follows:

First, for the best individual historical value of each particle position selection :

1), Combined with the current population and particle optima of population;

2), Calculated for each individual particle history optimal value position and the current position of the fitness value;

3), If there is a relationship between two particles dominate, it will be one of the non-dominated optimal value as a historical individual position of each individual. If there is no dominance relationship, choose a small fitness value as a historical individual optimal value of each individual location.

Second, for the global optima choice:

1), Select the dominated individuals for each individual from the outside population.

2), Select the optimal value of the position for each particle for govern their individual.

Last, for the choice of the weights ω , according adaptive thought, proposed a new method to calculate the velocity weighting ω . The specific mathematical description:

From:

$$\begin{gathered} v_i = \omega * v_i + c_1 * rand * (pbest_i - x_i) + c_2 * rand * (gbest_i - x_i) \\ x_i = x_i + v_i \end{gathered} \quad (7)$$

Change to:

$$\begin{aligned} & v_i = \omega_i * v_i + c_1 * rand * (pbest_i - x_i) + c_2 * rand * (gbest_i - x_i) \\ & x_i = x_i + v_i \end{aligned} \quad (8)$$

$$\omega_i = \begin{cases} \omega_{\max} & f_i > f_{av1} \\ \omega_{\max} - \dfrac{(\omega_{\max} - \omega_{\min})(f_{av1} - f_i)}{f_{av1} - f_{av2}} & f_{av2} \le f_i \le f_{av1} \\ \omega_{\min} & f_i < f_{av2} \end{cases}$$

Where: $P = [s, p_1, p_2, ..., p_n, e]$ is each particle's fitness value at present. f_{av1} is the average fitness value of the particles who greater than the population average fitness; f_{av1} is the average fitness value of the particles who less than the population average fitness; c_1, c_2 are learning factor;

$\omega_{\max}, \omega_{\min}$ are the maximum and minimum velocity weighting ; $rand$ is a random number between 0 and 1; The flowchart of standard MOPSO Fig. (**1**):

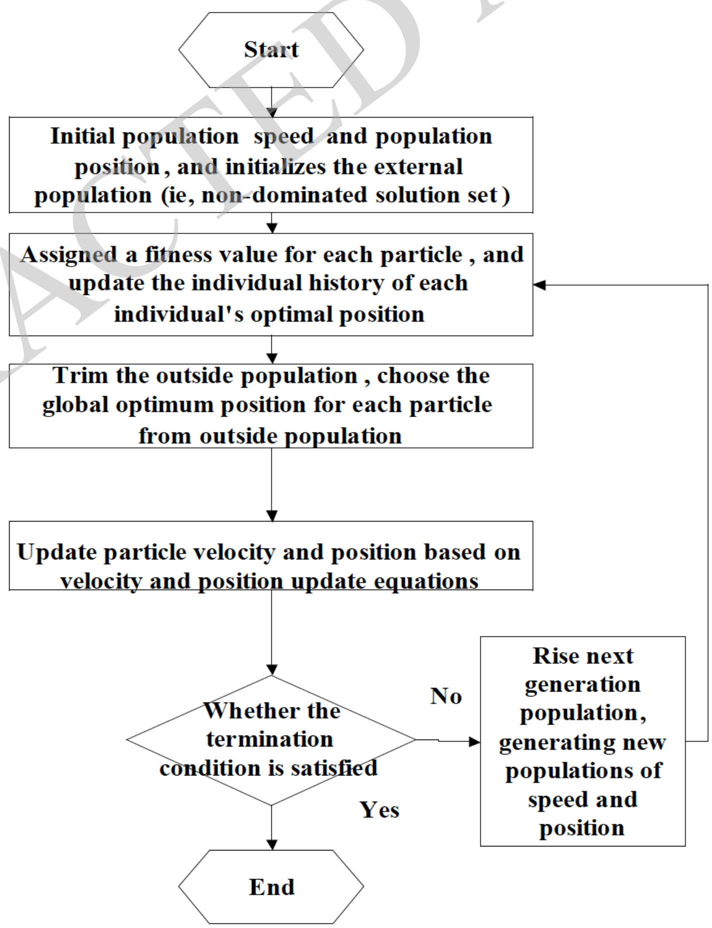

Fig. (1). The flowchart of standard MOPSO.

4. SIMULATION RESULTS

4.1. Simulate Verification in Classical Test Functions

In order to verify the improved performance of the proposed algorithm, This paper chose four commonly used test functions that is Schaffer function, Schaffer2 function, ZDT4 function and change the function of ZDT4 for simulation. This paper adopts two convergence index to verification the feasible and effective of improved algorithm. The four functions are as follows:

Schaffer function：

$$\min\ F(x)=(f_1(x),f_2(x))$$
$$f_1(x)=x^2$$
$$f_2(x)=(x-2)^2$$
$$-3\le x\le 3$$

Schaffer2 function：

$$\min\ F(x)=(f_1(x),f_2(x))$$
$$f_1(x)=\begin{cases}-x, & if\ x\le 1\\ -2+x, & if\ 1<x\le 3\\ 4-x, & if\ 3<x\le 4\\ -4+x, & if\ x>4\end{cases}$$
$$f_2(x)=(x-5)^2$$
$$-5\le x\le 10$$

ZDT4 function：

$$\min\ F(x_1,x_2)=(f_1(x_1,x_2),f_2(x_1,x_2))$$
$$f_1(x_1,x_2)=x_1$$
$$f_2(x_1,x_2)=g(x_1,x_2)[1-\sqrt{x_1/g(x_1,x_2)}]$$
$$g(x_1,x_2)=11+10\mathrm{n}+\sum_{i=2}^{n}(x_i^2-10\cos(4\pi x_i))$$
$$-5\le x_1\le 5$$
$$0\le x_2,\cdots,x_n\le 1, n=10$$

Changed ZDT4：

$$\min\ F(x_1,x_2)=(f_1(x_1,x_2),f_2(x_1,x_2))$$
$$f_1(x_1,x_2)=x_1$$
$$f_2(x_1,x_2)=g(x_1,x_2)[1-\sqrt{x_1/g(x_1,x_2)}]$$
$$g(x_1,x_2)=11+10\mathrm{n}+\sum_{i=2}^{n}(x_i^2+10\cos(4\pi x_i))$$
$$-5\le x_1\le 5$$
$$0\le x_2,\cdots,x_n\le 1, n=10$$

Parameter setting in Indicators one：

learning factor： $c1=c2=1.47$ ；

velocity weighting： $\omega=0.8,\omega_{\min}=0.2,\omega_{\max}=0.9$;

Maximum and minimum speed：Plus or minus fifty percent of the maximum displacement；

Population size： $popsize=20,20,50,80$;

The maximum number of iterations:

$Max\_gen=100,80,100,70$;

External archive： $NDSet=50$ ；

Fig. (**2**) is Pareto optimal boundary map of each test functions.

From the structure and the Pareto optimal boundary maps of four test functions, we know:

Schaffer function: External archive particles have a better distribution and diversity; Function has two objective functions; each objective function is one-dimensional; and each function has only one minimum point; Function is relatively simple.

Schaffer2 function: External archive particles have a better distribution and diversity; Function has two objective functions; Each objective function is one-dimensional; And each function has only one minimum point; This function is a piecewise function what Pareto optimal boundary is not contiguous; Comparison Schaffer function complex function, But not great complexity.

ZDT4 function: External archive particles have a better distribution and diversity; Function has two objective functions, first objective function is a linear function of changes in one dimension and no extreme points, Second objective functions with multiple extreme points and multi-dimensional, Function is relatively complex.

Changed ZDT4 function: External archive particles have a better distribution and diversity; Function has two objective functions, first objective function is a linear function of changes in one dimension and no extreme points, Second objective functions with multiple extreme points and multi-dimensional, Function is relatively complex.

From Figs. (**3-6**) are convergence performance comparison charts of MOPSO and improvements MOPSO.

From Fig. (**3**) to Fig. (**6**), it shows that: Schaffer function: in the iteration time, before and after the algorithm improvement, algorithms are able to quickly converge to Pareto optimal boundary, the performance of the improved algorithm is improved, but the performance is not very obvious.

Schaffer2 function: in the iteration time, before and after the algorithm improvement, algorithms are able to quickly converge to Pareto optimal boundary, the performance of the improved algorithm is improved and shows clearly.

ZDT4 function: in the improved particle swarm in front, algorithm in the iteration number is 20 began to converge to the Pareto optimal frontier; in the improved particle swarm, algorithm in the iteration number is 7 began to converge to the Pareto optimal frontier.

Changed ZDT4 function: in the improved particle swarm in front, algorithm in the iteration number is 42 began to converge to the Pareto optimal frontier; in the improved particle swarm, algorithm in the iteration number is 8 began to converge to the Pareto optimal frontier.

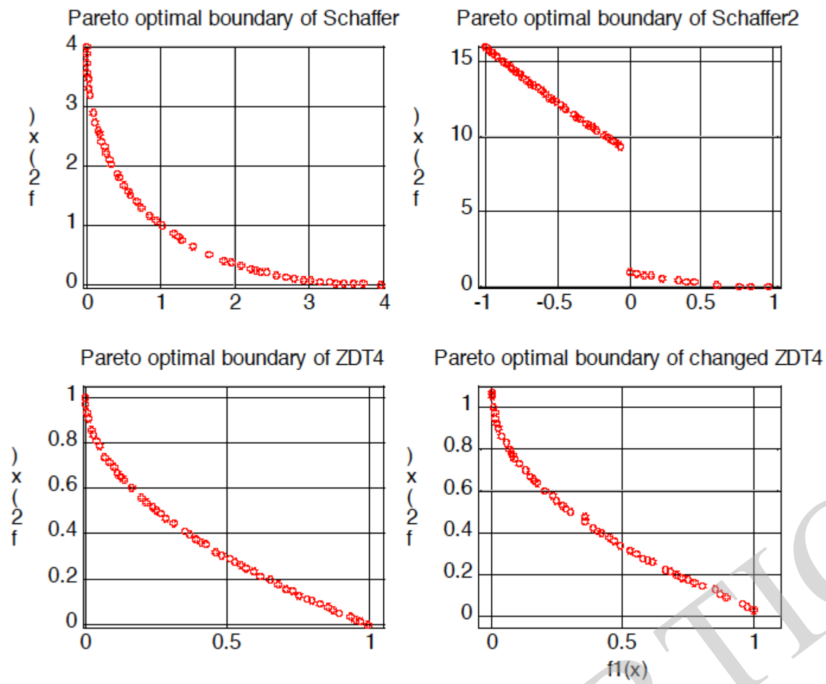

Fig. (2). Pareto optimal boundary maps of four test functions.

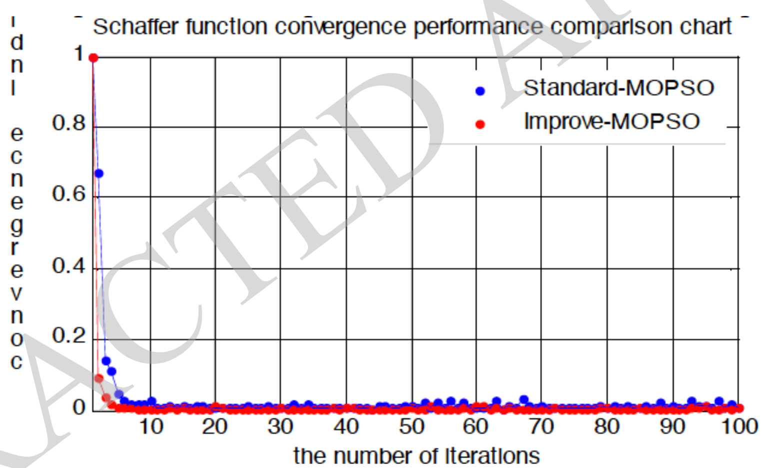

Fig. (3). Schaffer function convergence performance comparison chart.

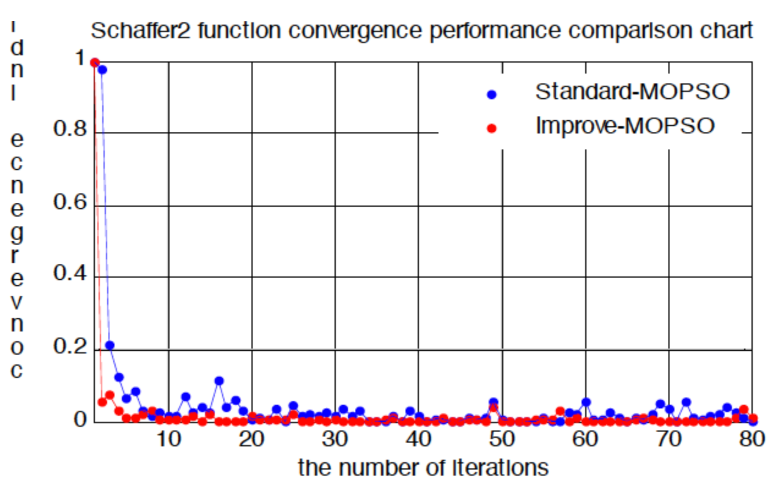

Fig. (4). Schaffer2 function convergence performance comparison chart.

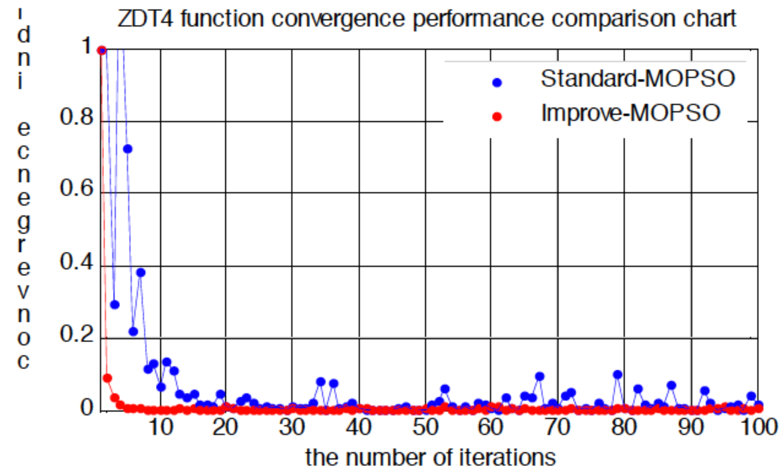

Fig. (5). ZDT4 function convergence performance comparison chart.

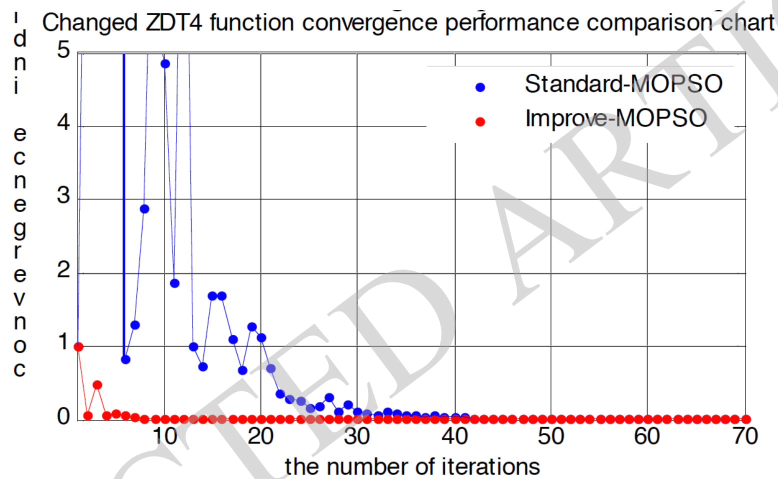

Fig. (6). Changed ZDT4 function convergence performance comparison chart.

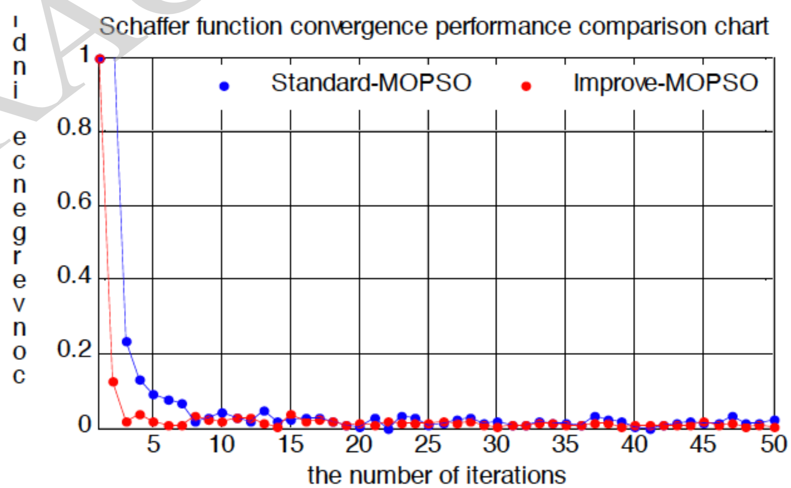

Fig. (7). Schaffer function convergence performance comparison chart.

Parameter setting in indicators two：

learning factor：$c1 = c2 = 1.47$， velocity weighting：$\omega = 0.8, \omega_{\min} = 0.2, \omega_{\max} = 0.9$;Maximum and minimum speed: Plus or minus fifty percent of the maximum displacement; Population size：$popsize = 20, 20, 50, 80$ ； The maximum number of iterations:

$Max\_gen =$ 50, 50, 70, 500 ；

External archive：$NDSet = 50$.

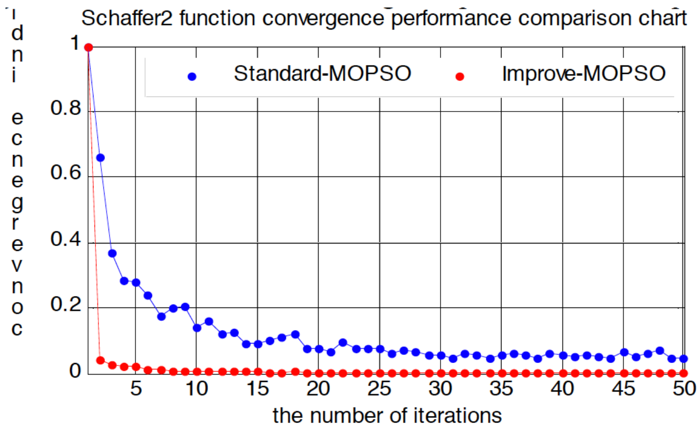

Fig. (8). Schaffer2 function convergence performance comparison chart.

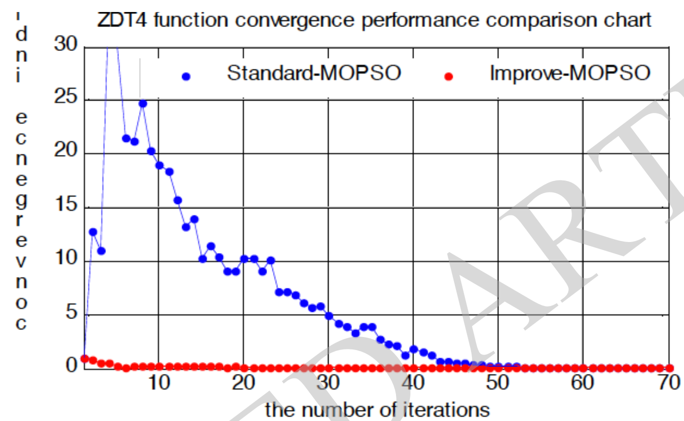

Fig. (9). ZDT4 function convergence performance comparison chart.

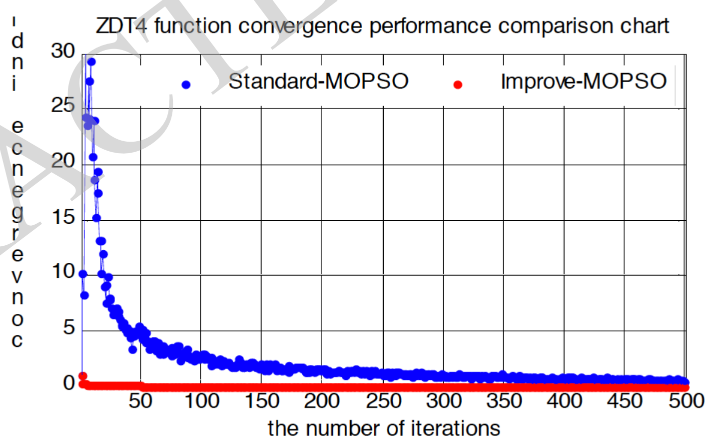

Fig. (10). Changed ZDT4 function convergence performance comparison chart.

From Figs. (**7**-**10**) are convergence performance comparison charts of MOPSO and improvements MOPSO.

Schaffer function: in the iteration time, before and after the algorithm improvement, population particles are able to quickly converge to Pareto optimal boundary, the performance of the improved algorithm is improved, but the performance is not very obvious.

From Fig. (**7**) to Fig. (**10**), we know:

Schaffer2 function: in the iteration time, before and after the algorithm improvement, population particles are able to quickly converge to Pareto optimal boundary, the performance of the improved algorithm is improved and shows clearly.

ZDT4 function: in the improved particle swarm in front, population particles in the iteration number is 20 began to converge to the Pareto optimal frontier; in the improved particle swarm, population particles in the iteration number is 7 began to converge to the Pareto optimal frontier.

Changed ZDT4 function: in the improved particle swarm in front, population particles in the iteration number is 450 began to converge to the Pareto optimal frontier; in the improved particle swarm, population particles in the iteration number is 50 began to converge to the Pareto optimal frontier.

From the eight convergence performance charts and their results analysis we know: by introducing the improved method to MOPSO not only let the Population particle can quickly find and convergence to the Pareto optimal frontier but also let the algorithm can quickly find and convergence to the Pareto optimal frontier. Especially when the target function with multiple extreme points is complicated what can be seen in Fig. (**4**), Fig. (**5**), Fig. (**8**) and Fig. (**9**). The feasibility and effectiveness of the algorithm improvement in multi-objective problems has been verified.

CONCLUSION

In this paper, by reading the relevant literature on multi-objective particle swarm algorithm and analysis the difficult points of multi-objective particle swarm optimization algorithm propose some improvement of MOPSO what is based on the thoughts of SPEA2 and the ideas of adaptive. According the simulation result verification of classical test functions and the application research in robot path, we have drawn the following conclusions:

Improved algorithm enhances the information transfer strength of the population particles what makes the whole population is able to quickly find and convergence to the Pareto optimal frontier.

Improved algorithm makes the population particle can jump out of local optimum what makes the performance of the algorithm have some improve that is the improved algorithm can quickly find and convergence to the Pareto optimal frontier.

CONFLICT OF INTEREST

The authors confirm that this article content has no conflict of interest.

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