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ICIC 2011 Paper #1348 Decision Notification

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Dear Author(s)

Congratulations! On behalf of the ICIC 2011 International Program Committee, we are very pleased to inform you that your paper:

Paper ID: **1348**
Author(s): **Yanxia Sun, Barend Jacobus van Wyk, Zenghui Wang**
Title: **A New Multi-swarm Multi-objective Particle Swarm Optimization based on a Pareto Front Set**
Presentation: **oral**

has been accepted for presentation at the 2011 International Conference on Intelligent Computing, which has been selected into the following Springer volume:

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If you require a visa to enter China please send a request for an invitation letter to Prashan Premaratne, University of Wollongong, Australia at prashan@uow.edu.au. Thank you for participating in ICIC 2011. We look forward to seeing you in Zhengzhou, China, August 11-14, 2011.

Sincerely,

ICIC2011 Program Committee

REVIEWERS' COMMENTS

REVIEW NO. 1

Originality: 4
Significance of topic: 4
Technical quality: 4
Relevance to ICIC 2011: 3.5
Presentation: 3.5

Overall rating: 3.8
Reviewer's expertise on the topic: High

Comments to the authors:
The idea of using several swarms to search the objective space around the Pareto front set for MOPSO is novel, and this paper has a good structure. But there are some problems in the paper. In view of that, I will give you some suggestions as below.
1. Rn in section 2 should be Rm.
2. Please define the R1, R2 and R3.
3. The formula m=floor() is error or the definition of numg is error. Please modify it.

REVIEWERS' COMMENTS

REVIEW NO. 2

Originality: 3.5
Significance of topic: 5
Technical quality: 4
Relevance to ICIC 2011: 4
Presentation: 5
Overall rating: 4.3
Reviewer's expertise on the topic: Medium

Comments to the authors:
This paper proposed a multi-swarm particle
swarm optimization. Simulation results and
comparisons with existing Multi-objective Particle Swarm Optimization methods demonstrate that the effectiveness of the proposed method.
There are some problems as below:
1、There isn't Fig.1 in the paper.
2、In page 7, '5.2 Performance Metrics' should be '4.2 Performance Metrics'.

REVIEWERS' COMMENTS

REVIEW NO. 3

Originality: 3.5
Significance of topic: 4
Technical quality: 3
Relevance to ICIC 2011: 3
Presentation: 2.5
Overall rating: 3.2
Reviewer's expertise on the topic: High

Comments to the authors:
-The sentence in the paper should be improved.
-And some mistakes should be amended. For example, 'iff' should be 'if'.
-In the paper, there are no other's literature computational result about the test functions. The author could compare computational result with other literature.

Comments of PC Member:

A New Multi-swarm Multi-objective Particle Swarm Optimization Based on Pareto Front Set

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Abstract. In this paper, a new multi-swarm method is proposed for multi-objective particle swarm optimization. To enhance the Pareto front searching ability of PSO, the particles are divided into many swarms. Several swarms are dynamically searching the objective space around some points of the Pareto front set. The rest of particles are searching the space keeping away from the Pareto front to improve the global search ability. Simulation results and comparisons with existing Multi-objective Particle Swarm Optimization methods demonstrate that the proposed method effectively enhances the search efficiency and improves the search quality.

Keywords: Multi-objective Optimization, Particle Swarm Optimization, Multiple swarms, Pareto front.

1 Introduction

The particle swarm optimization (PSO), first introduced by Kennedy et al. [1], is a stochastic optimization technique that can be roughly linked to the behavior of a flock of birds or the sociological behavior of a group of people. Due to its simple mechanism and high performance for global optimization, PSO has been applied to many optimization problems successfully [2][3]. However, many real-world optimization problems involve optimizing multiple non-commensurable and often competing criteria that reflect various design specifications and constraints [4]. Researchers regard PSO as a very strong competitor to other algorithms in solving multi-objective optimal problems. However, such a feature is also a demerit in optimal problems involving multimodal objective functions, since the information sharing will also degrade the diversity of the algorithm and reduce the global searching ability of the algorithm [2].

In contrast to single-objective optimization, it is essential to obtain a well-distributed and diverse solution set for finding the final tradeoff in multi-objective optimization. Some algorithms such as the non-dominated sorting genetic algorithm (NSGA-II) [5], the strength Pareto evolutionary algorithm (SPEA2) [6], multi-objective PSO (MOPSO) [7], have been proposed. During the evolutionary multi-objective optimization, it is often desired to distribute the solution points or individuals as diversely as possible on the discovered trade-offs. In addition, the

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uniformity among the distributed points or individuals is also an important issue in order to ensure consistent transition among the solution points when searching for the most suitable solution from the best possible compromise. Some multi-swarm multi-objective particle swarm optimization (MMPSO) methods were proposed to achieve a better optimization performance. Unlike what biology indicates in mixed species flocking that the number of species involved varies dynamically, some of these multiple-swarm PSOs [8][9] adopt the notion of using a heuristically chosen number of swarms with a fixed swarm size throughout the search process. However, some multiple-swarm PSO algorithms, such as reference [10] [11], used the adaptive swarm size methods. However, the existing MMPSOs do not use the information of Pareto front to allocate the swarms. And it is very possible to find good results if the particles search around the Pareto front found.

This paper proposes a new Multi-swarm multi-objective particle swarm optimization method. In this method, the particles are divided into several swarms, which can be called Pareto front swarms as they search the space around some points of Pareto front set. The rest of this paper is arranged as follows: Section 2 introduces multi-objective particle swarm optimization. Section 3 proposes the dynamic new multi-swarm method. Section 4 describes the problems used to evaluate the new algorithm and the results obtained. Finally, the concluding remarks appear in Section 5.

2 A Brief Description of Multi-objective Particle Swarm Optimization

A single objective optimization algorithm will normally be terminated upon obtaining an optimal solution. However, for most realistic multi-objective problems, there can be a number of optimal solutions. Suitability of one solution depends on a number of factors including user's choice and problem environment, and hence finding the entire set of optimal solutions may be desired. Many real-world applications involve complex optimization problems with various competing specifications. In general, a multi-objective optimization problem can be described as:

$$\text{Min } F(x) = (f_1(x), \cdots, f_m(x)) . \qquad (1)$$
$$\text{Subject to } x \in \Omega .$$

Here Ω is the decision (variable) space, R^m is the objective space, and $F : \Omega \to R^m$ consists of m real-valued objective functions. If Ω is a closed and connected region in R^m and all the objectives are functions of x, we call problem (1) as a continuous multi-objective optimization (MOO).

In the total absence of information regarding the preference of objectives, a ranking scheme based upon the Pareto optimality is regarded as an appropriate approach to represent the fitness of each individual for MOO [12]. The solution to the MOO problem exists in the form of an alternate tradeoff known as a Pareto optimal set. Each objective component of any non-dominated solution in the Pareto optimal set can only be improved by degrading at least one of its other objective components. A vector F_a is said to dominate another vector F_b, denoted as

$F_a < F_b$, if and only if $f_{a,i} \le f_{b,i} \quad \forall i = \{1, 2, \cdots, m\}$
and $\exists j \in \{1, 2, \cdots, m\}$ *where* $f_{a,i} < f_{b,i}$.

For the more details related to MMPSO, please refer to reference [7].

3 Dynamic Multi-swarm Multi-objective Particle Swarm Optimization

Although a good algorithm design would guarantee a high probability of finding the Pareto optimal set, the number of swarms with a fixed swarm size indirectly contributes to the effectiveness and efficiency of an algorithm's performance, particularly from the viewpoint of the computational cost. If a multiple-swarm PSO employs an overly large number of swarms with a fixed swarm size, it will enjoy a better chance of discovering possible good solutions that lead to the optimal Pareto set, but inevitably suffer from an undesirable computational cost. On the other hand, an insufficient number of swarms will undermine chances of exploring the search space to discover potential good solutions, and coupled with PSO's high speed in convergence. This may lead to undesirable premature convergence or result in degraded quality of the optimal Pareto set. There are existing publications that attempt to address this deficiency. Unlike what biology indicates in mixed species flocking that the number of species involved varies dynamically, some of these multiple-swarm PSOs [8][9] adopt the notion of using a heuristically chosen number of swarms with a fixed swarm size throughout the search process. However, some multiple-swarm PSO algorithms, such as reference [10] [11], used the adaptive swarm size methods. However, the existing MMPSOs do not use the information of Pareto front to allocate the swarms. And it is very possible to find good results if the particles search around the Pareto front, which is already found, as the new Pareto front points are sometimes near the old Pareto front points.

Motivated by these studies, we propose a new multi-swarm multi-objective optimization method. Firstly, several swarms are used to search a certain region around certain points of Pareto front set. These swarms are called Pareto front swarms. The other particles, which compose the spare swarm, search other spaces far away from the Pareto front to make sure all the particles spread around the objective space. The contributions of the algorithm are as follows.

Pareto front swarms are encouraged to explore different regions around some points of Pareto front, according to the following equations:

$$V_i(t+1) = \omega V_i(t) + c_1 R_1 (P_i - X_i(t)) + c_2 R_2 (P_g - X_i(t)) + c_3 R_3 (Core(m) - X_i(t)) \tag{2}$$

$$X_i(t+1) = X_i(t) + V_i(t+1) \tag{3}$$

Here, R_1, R_2 and R_3 are two random weights whose components r_1^j and r_2^j $(j = 1, 2 \cdots, n,)$ are chosen uniformly within the interval $[0,1]$, $Core(m)$ is central point of the m^{th} swarm and is chosen dynamically, the relationship between m and i is $m = \text{floor}(i / num_g) + 1$, num_g is the particle number of the Pareto front swarm and $\text{floor}(A)$ rounds the elements of A to the nearest integers less than or equal to A. The number of the cores equals the number of the Pareto front swarms. The cores are selected the same way that the Pareto front, thus, the diversity is preserved.

2) The particles of the spare swarm, whose members are the rest of particles, are updated using

$$V_i(t+1) = \omega V_i(t) + c_1 R_1 (P_i - X_i(t)) + c_2 R_2 (P_g - X_i(t)) - c_4 R_4 (Core(m) - X_i(t)) \quad (4)$$

$$X_i(t+1) = X_i(t) + V_i(t+1) \quad (5)$$

Here, c_4 is determined by the sharing function [13] according to the distance between particle *i* and core particles,

$$R_4 = \frac{1}{m_g} rand(\cdot) \quad (6)$$

and m_g is the number of Pareto front swarms.

3) To prevent the premature of the whole particles and keep the fast convergence property of PSO, small disturbance is added to one component of the particle vector of the spare swarm in a random way, that is,

$$V_i(t+1, irand) = V_i(t+1, irand) + \frac{R_v}{m_g} \quad (7)$$

Here, R_v is a random number within an interval of $[-1,1]$.

The method of choosing P_i and P_g is using the method of ref. [15].

The following procedure can be used for implementing the proposed particle swarm algorithm:

1) Initialize the parameters of particles and swarm by assigning a random position in the problem hyperspace to each particle.
2) Evaluate the fitness functions for each particle.
3) Find the non-dominated Pareto front and store them in the repository set.
4) Determine the cores of Pareto front swarms.
5) Using (2) and (3); or (4), (7) and (5) to update the positions of particles.
6) Repeat steps (2)-(6) until a stopping criterion is met (e.g., maximum number of iterations or a sufficiently good fitness value).

4 Comparison between the Proposed Method and Other Multi-objective Optimization Methods

4.1 Test Problems

The test problems are ZDT1, ZDT2, ZDT3 [5]. The Pareto front of ZDT1 is convex. The Pareto front of ZDT2 is non-convex. The Pareto front of ZDT3 is non-convex and disconnected. They are very typical benchmark functions. The real Pareto fronts of these three optimization problems are located on the objective value with $x_1 \in [0,1]$ and $x_i = 0(i = 2,\cdots n)$.

In this section, the performance of this proposed method is compared with the no group method and the existing result in ref. [10]. In these examples, the total number of fitness function evaluations was set to 50 000. The particle number is 200. The number of Pareto front swarms is 15. A random initial population was created for each of the 20 runs on each test problem. The maximum number of external repository particles is 100. Parameters are set as $c_1 = c_2 = 2$ and $\omega = 0.5 + rand(\bullet)$.

Using the proposed method, the Pareto fronts are the red 'o' line in Fig. 1, 2 and 3, respectively. If the particles are not divided into several groups and the multi-objective PSO in reference [15] is used, the Pareto front is the blue '*' which is blue in the online version in Fig. 1. As can be seen from Fig. 1, the proposed method can achieve a good optimization performance the no group method.

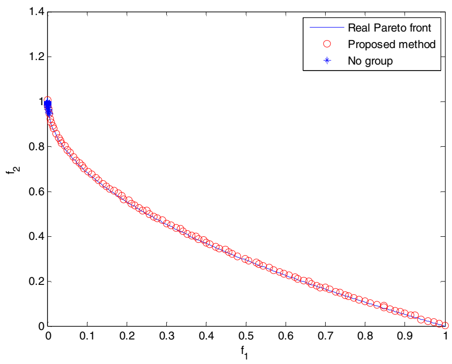

Fig. 1. Pareto front for ZDT1

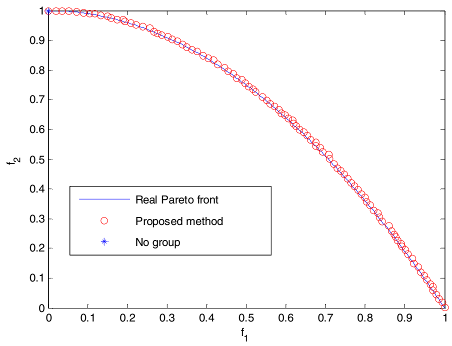

Fig. 2. Pareto front for ZDT2

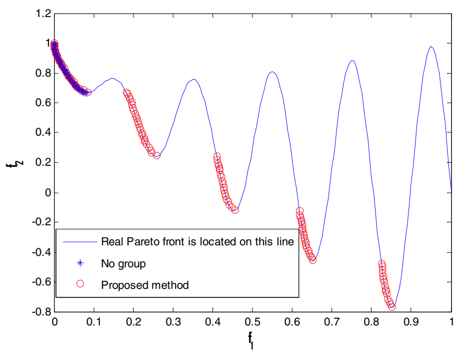

Fig. 3. Pareto front for ZDT3

From Figs. 1, 2 and 3, it can be seen that the proposed method is greatly improved compared with the algorithms which do not use the groups. For this simulation result, the main reason is that the multi-objective PSO suffers from premature convergence.

4.2 Performance Metrics

In order to provide a quantitative assessment for the performance of MO optimizer, two metrics are often taken into consideration, i.e., Generational Distance and Spacing metric [7, 15].

1) The metric of generational distance (GD) gives a good indication of the gap between the discovered Pareto front and the true Pareto front [7], which is given by

$$GD = \frac{\sqrt{\sum_{i=1}^{n} d_i^2}}{n}, \tag{14}$$

where n is the number of vectors in the set of non-dominated solutions found so far and d_i is the Euclidean distance (measured in objective space) between each of these and the nearest member of the Pareto optimal set.

The GD comparison of the proposed method and the no group optimization method is shown in Table 1.

Table 1. Comparison of the proposed method and the no group optimization method

Performance \ Test Problem		ZDT1	ZDT2	ZDT3
No Group Method	min	0 (Pareto front converges to one point)	0 (Pareto front converges to one point)	0.0011
	mean	0.0023	9.9598×10^{-6}	0.0025
	max	0.0048	4.9799×10^{-5}	0.0042
	std	0.0023	1.9920×10^{-5}	0.0012
Proposed method	min	2.571×10^{-4}	9.935×10^{-5}	9.870×10^{-5}
	mean	2.836×10^{-4}	3.015×10^{-4}	1.612×10^{-4}
	max	3.239×10^{-4}	3.164×10^{-4}	2.228×10^{-4}
	std	8.160×10^{-6}	5.186×10^{-5}	5.275×10^{-4}

2) To measure the distribution of vectors throughout the non-dominated vectors found so far, the spacing metric is often used [7], which is given by

$$S \triangleq \sqrt{\frac{1}{n-1}\sum_{i=1}^{d}(\bar{d}-d_i)^2}, \tag{15}$$

where $d_i = \min_j(\left|f_1^i(\vec{x}) - f_1^j(\vec{x})\right| + \left|f_2^i(\vec{x}) - f_2^j(\vec{x})\right|)$, $i, j = 1,\cdots,n$, $\bar{d}$ is the mean of all d_i and n is the number of nondominated vectors found so far. This metric can show how well the Pareto front found is if all the points are on or very close to the real Pareto front. At this situation, the smaller the spacing metric is, the better the particles are spread along the Pareto front. It would be better to use the spacing metric together with the Pareto front figure; otherwise it would be difficult to conclude the performance just according to the spacing metric. For example, in Fig. 2, the space metric is 0.038 using the no group method; and the space metric is 0.0032 using the proposed method. Using the no group method, it was found all the Pareto front points converged to one point and the space metric is 0 in one simulation.

Table 2. Spacing comparison of the proposed method and the no group optimization method

Test Problem / Performance		ZDT1	ZDT2	ZDT3
No Group method	min	0 (Pareto front converges to one point)	0 (Pareto front converges to one point)	0.0361
	mean	0.0230	5.6e-004	0.0535
	max	0.0472	0.0028	0.0940
	std	0.0211	0.0011	0.0206
Proposed method	min	0.0031	0.0032	0.0038
	mean	0.0038	0.0035	0.0045
	max	0.0046	0.0040	0.0052
	std	1.946×10^{-4}	2.925×10^{-4}	5.271×10^{-4}

As can be seen from the statistic tables 1 and 2, the proposed method can achieve better Pareto front. From Table 2, we can also find that the proposed method can also achieve a better optimization performance than the MO-TRIBES based adaptive multi-objective particle swarm optimization algorithm. For the ZT1, ZT2 and ZT3 test functions, the average function values of 10 runs of the proposed method and the MO-TRIBES [10] are 0.0038, 0.0035, 0.0045 and 0.0047, 0.013, 0.0336. By comparing the results, it is seen that result using the proposed method is more stable the MO- TRIBES.

5 Conclusion

A new dynamic multi-swarm multi-objective particle swarm optimization was proposed. For this method, the particles were divided into multiple swarms. The cores of multiple warm members were changed according to the new Pareto front. The proposed MMPSO method can improve the performance of standard MPSO and can be easily introduced to any other existing evolution methods. Simulation also showed that the optimization performance was improved compared with the no group method and the MO-TRIBES based adaptive multi-objective particle swarm optimization algorithm.

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