Multi-Swarm Particle Swarm Optimization with Multiple Learning Strategies

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ABSTRACT

Inspired by the division of labor and migration behavior in nature, this paper proposes a novel particle swarm optimization algorithm with multiple learning strategies (PSO-MLS). In the algorithm, particles are divided into three sub-swarms randomly while three learning strategies with different motivations are applied to each sub-swarm respectively. The Traditional Learning Strategy (TLS) inherits the basic operations of PSO to guarantee the stability. Then a Periodically Stochastic Learning Strategy (PSLS) employs a random learning vector to increase the diversity so as to enhance the global search ability. A Random Mutation Learning Strategy (RMLS) adopts mutation to enable particles to jump out of local optima when trapped. Besides, information migration is applied within the intercommunication of sub-swarms. After a certain number of generations, sub-swarms would aggregate to continue search, aiming at global convergence. Through these learning strategies and swarm aggregation, PSO-MLS possesses both good exploration and exploitation abilities. PSO-MLS was tested on a set of benchmarks and the result shows its superiority to gain higher accuracy for unimodal functions and better solution quality for multimodal functions when compared to some PSO variants.

Categories and Subject Descriptors

I.2.8 [**Artificial Intelligence**]: Problem Solving, Control Methods, and Search – *heuristic methods*.

General Terms

Algorithms, Performance, Experimentation.

Keywords

Particle swarm optimization, division of labor, multiple learning strategies, migration, aggregation

1. INTRODUCTION

Particle Swarm Optimization (PSO) is a population-based stochastic optimization technique developed by Eberhart and Kennedy in 1995 [1]. PSO can find the global optimal rapidly when solving unimodal problems. But people have found that the fast loss of swarm diversity during the course of evolution causes PSO plunge into local optima and leads to premature convergence when solving complex multimodal problems.

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Aiming at balancing PSO's searching stability and diversity, this paper proposes a novel multi-swarm particle swarm optimization algorithm with multiple learning strategies (PSO-MLS) which is inspired by the biological labor cooperation knowledge in nature. In order to emulate labor cooperation behavior, PSO-MLS maintains multi-swarms instead of one population to conduct optimization. The initialized particles are divided into three populations of equal size randomly. Three learning strategies, i.e., the Traditional Learning Strategy (TLS), the Periodically Stochastic Learning Strategy (PSLS), and the Random Mutation Learning Strategy (RMLS) which correspond to different labor cooperation motivations are applied to sub-swarms respectively. TLS inherits the basic operations of PSO to ensure the stability of PSO-MLS; PSLS employs a random guiding vector periodically to broaden the search field of vision and thus add to the diversity of particles; RMLS adopts random mutation to help the population jump out of the local optimum when trapped. Furthermore, sub-swarms exchange information through a migration strategy which is called Information Migration Strategy (IMS). Besides, after a certain number of generations, sub-swarms would aggregate into a whole swarm to continue search in order to guarantee the global convergence. Through the above mechanisms, the proposed algorithm is able to keep both good exploration and exploitation abilities. Experimental results on benchmarks are compared with another two PSO variants, which show the effectiveness and efficiency of PSO-MLS as it could achieve higher accuracy for unimodal functions as well as improve the solution quality for complex multimodal functions.

2. MULTI-SWARM PARTICLE SWARM OPTIMIZATION WITH MULTIPLE LEARNING STRATEGIES (PSO-MLS)

Detailed design of the PSO algorithm is not presented here due to page limit. In this section, we focus on introducing the implementation of multiple learning strategies in the algorithm.

2.1 Strategy for Sub-swarm A: Traditional Learning Strategy (TLS)

TLS inherits the basic updating method of original PSO i.e. (1) and (2) with linearly decreasing weight ω from 0.9 to 0.4 [2]. Sub-swarm A inherits the basic operation of traditional PSO and thus maintains the general search behavior of PSO, which ensures the fundamental support for PSO-MLS algorithm.

$$\begin{aligned} V_{id} = \omega * V_{id} + c_1 * rand_1 * (pbest_{id} - X_{id}) \\ + c_2 * rand_2 * (gbest_{id} - X_{id}) \end{aligned} \tag{1}$$

$$X_{id} = X_{id} + V_{id} \tag{2}$$

2.2 Strategy for Sub-swarm B: Periodically Stochastic Learning Strategy (PSLS)

Focusing on increasing searching diversity and exploitation, PSLS employs a random learning vector based on three gbest positions found by three sub-swarms according to (3) and (4) in every certain generations. PSLS unites a third stochastic learning position periodically to make evolution thus enhance the diversity and increases the possibility to seek solutions of higher quality.

$$\begin{aligned} V_{id} = \omega * V_{id} &+ rand(0,c_1)*(pbest_{id} - x_{id}) \\ &+ rand(0,c_1)*(gbest_{id} - x_{id}) \\ &+ rand(0,c_1)*(xrand_{id} - x_{id}) \end{aligned} \tag{3}$$

$$xrand_{id} = rand(-2,2)*(xbest_1 + xbest_2 + xbest_3)/3 \tag{4}$$

When the generation doesn't meet with the period to adopt PSLS, particles in sub-swarm B apply TLS. Adopting PSLS at regular intervals pushes particles in the sub-swarm to broaden their vision fields of searching, increasing the possibilities to find better peaks.

2.3 Strategy for Sub-swarm C: Random Mutation Learning Strategy (RMLS)

For the sake of pushing particles to not plunge into narrow searching space and trap into local optima, two particles are selected from sub-swarm C (should excludes its best particle) randomly every generation and takes RMLS strategy. RMLS employs random velocity mutation according to (5) to force particles to change flying velocity and hence change the current search directions abruptly to search different regions.

$$V_{id} = V_{id} * rand(-2,2) \tag{5}$$

2.4 Strategy for all Sub-swarms: BW strategy

In order to exchange information among sub-swarms, migration is applied to sub-swarms. In paper [3], results show that the BW strategy which migrates the best particles from source subpopulation and replace the worst particles of destination subpopulation is very efficient. So we choose BW for IMS to exchange the information and the number of best particles and worst particles are both set to one to maintain the stability of the entire population. The best particle of sub-swarm A, C and B, respectively, replaces the worst particle of sub-swarm C, B and A.

2.5 Population Aggregation Behavior

In order to guarantee the convergence of PSO-MLS, three sub-swarms would recombine into one whole population after the evolution finishes first 80% generations, and adopts constriction coefficient [4] to update velocity as (6), where φ is set to 0.729, c is set to 2.05 to ensure convergence.

$$\begin{aligned} V_{id} = \varphi * (V_{id} &+ c * rand_1 * (pbest_{id} - x_{id}) \\ &+ c * rand_2 * (gbest_{id} - x_{id})) \end{aligned} \tag{6}$$

In the first 80% generations, three sub-swarms had concentrated on possessing good global exploration and local exploitation through combining different strategies. When it comes to the finishing stage, the entire population should focus on keeping continuous convergence to a great extent. And constriction coefficient for velocity update is exactly in accordance with fast convergence.

3. EXPERIMENTAL RESULTS

PSO-MLS is tested on 13 different benchmark functions [5]. It is further compared with the traditional global version PSO and DMS-PSO [6]. For each function, 30 trials are carried out with population size 30. The statistical results including the best, mean and standard deviations of the error values, verify PSO-MLS's superiority and robustness to gain higher accuracy for unimodal functions and better solution quality for multimodal functions. Due to page limit, the Table 1 shows the best error values only.

Table 1 Comparison of Best Results for the Three Algorithms

fun.	GPSO	DMS-PSO	PSO-MLS
f_1	2.01e-64	5.19e-68	**2.56e-92**
f_2	4.20e-42	6.58e-40	**2.01e-49**
f_3	0.00170	1.82062	**7.33e-07**
f_4	0.03123	0.07709	**2.73e-08**
f_5	0.107	0.289	**5.33e-05**
f_6	**0**	**0**	**0**
f_7	0.00272	0.00451	**0.00112**
f_8	1835.82	2645.17	**1618.68**
f_9	11.9395	13.9294	**5.96975**
f_{10}	6.96e-15	**3.41e-15**	**3.41e-15**
f_{11}	5.42e-20	5.42e-20	**0**
f_{12}	**1.57e-32**	**1.57e-32**	**1.57e-32**
f_{13}	**1.35e-32**	**1.35e-32**	**1.35e-32**

4. CONCLUSION

Based on division of labor and migration behavior in nature, a novel PSO algorithm with multiple learning strategies (PSO-MLS) is developed. The experimental results verify the high searching efficiency and robustness of PSO-MLS for both unimodal and multimodal functions. We will further investigate PSO-MLS, including designing more efficient learning strategies.

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