A Set-based Locally Informed Discrete Particle Swarm Optimization

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ABSTRACT
This paper proposed an efficient discrete PSO algorithm. Following the general process of the recently proposed locally informed particle swarm (LIPS), the velocity update of each particle in the proposed algorithm depends on the pbests of its nearest neighbors. However, in order to achieve optimization in discrete space, the related arithmetic operators and the concept of 'distance' in LIPS are redefined based on set theory. Thus, the proposed algorithm is termed Set-based LIPS (S-LIPS). Moreover, a reset scheme is embedded in S-LIPS to further improve population diversity in S-LIPS. By using the locally informed update mechanism and the reset scheme, the proposed algorithm is able to have both high convergence speed and good global search ability. S-LIPS is compared with a set-based comprehensive learning PSO on TSP benchmark instances. The experimental result shows that S-LIPS is a very promising algorithm for solving discrete problems, especially in the case where the scale of the problem is large.

Categories and Subject Descriptors
I.2.8 [**Artificial Intelligence**]: Problem Solving, Control Methods, and Search – *Heuristic methods*

General Terms
Algorithms, Performance, Design, Experimentation.

Keywords
evolutionary computation, particle swarm optimization, traveling salesman problems

1. INTRODUCTION
In evolutionary computation community, particle swarm optimization has attracted much attention. Recent decades have witnessed a great many emergences of PSO variants, like APSO[1], LIPS[2], CLPSO[3], which have significantly improved the original PSO. Meanwhile, the discretization of PSO has also attracted plenty of attention. Recently, W. N. Chen *et al*. [4] proposed a new framework of discrete PSO, the Set-based PSO (S-PSO). It defines the candidate solution as a *n*-tuple of crisp sets and the velocity as a *n*-tuple of sets with possibilities. S-PSO redefines the arithmetic operators. As the most suitable variant of S-PSO, the set-based comprehensive learning PSO (S-CLPSO) is shown to be very competitive.

However, the convergence speed of S-CLPSO is not satisfactorily fast enough, which can be seen in the comparison between ACS and S-CLPSO [4]. In contrast to CLPSO, LIPS has a higher convergence speed. Because its efficiency in detecting all optima, we make an attempt to discretize LIPS.

This paper proposes a new S-PSO, the set-based locally informed particle swarm (S-LIPS). S-LIPS shares the same frame with S-SPO and the velocity update depends on the pbests of several neighbors. However, in order to apply set-based operators to LIPS, the concept of 'distance' and the arithmetic operators are redefined. Moreover, a reset scheme is designed to increase the global search ability of LIPS. Judged from the test on various TSP instances, S-LIPS is very competitive because of its high convergence speed and satisfying global search ability.

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2. THE SET-BASED LOCALLY INFORMED PSO
The discretization of LIPS requires redefinitions of the arithmetic operators, which differs from the definitions in S-PSO.

(1). $\sum coefficient \times position$

Firstly, assign a random possibility to each element in the sets of a position, converting all the positions to velocities. Then we add the possibilities of the same element in velocities.

$$\begin{aligned} & V = \sum c_i X_i = (V^1, V^2, V^3 \ldots V^{n-1}, V^n) \\ & V^i = \{e, p(e) \mid e \in E^i\} \\ & p(e) = \sum c_i p_i(e) \\ & p_i(e) = \begin{cases} random(0,1) & e \in X_i^{\,j}, j = 1,2 \ldots n \\ 0 & e \notin X_i^{\,j}, j = 1,2 \ldots n \end{cases} \end{aligned} \tag{1}$$

(2). $velocity - position$

The positions are converted into velocities before the subtraction. Then the operation becomes a subtraction between velocities.

$$V_A - X_B = (V^1, V^2, V^3 ... V^{n-1}, V^n)$$
$$V^i = \{e, p'(e) \mid e \in E^i\}$$
$$p'(e) = \begin{cases} p_{V_A}(e) - p_{X_B}(e), & p_{V_A}(e) > p_{X_B}(e) \\ 0, & otherwise \end{cases} \quad (2)$$
$$p_{X_B}(e) = \begin{cases} random(0,1), & e \in X_B{}^j, j = 1,2..n \\ 0, & otherwise \end{cases}$$

(3). $velocity + velocity$

Given two velocities, V_1 and V_2, the summation of V_1 and V_2 is :

$$V_1 + V_2 = (V^1, V^2, V^3 ... V^{n-1}, V^n)$$
$$V^i = \{e, \max(p_1(e), p_2(e)) \mid e \in E^i\} \quad (3)$$

With the definitions above, the velocity updating rule in LIPS showed below could be accomplished in discrete space.

$$V_i^j = V_i^j + \omega(P_i^j - X_i^j)$$
$$P_i = \frac{1}{\varphi}\sum_{k=1}^{nsize}\varphi_k nbest_k \quad (4)$$

φ_k is a uniformly distributed random number and φ is the summation of φ_k . $nbest_k$ is the *k*th nearest neighbor's pbest to the *i*th particle. *nsize* is the neighborhood size. However, as Euclidean distance does not apply to problems in discrete space, we redefine the distance between two particles as follows:

$$dist(i,j) = |S|$$
$$S = \{e \mid e \in X_i^k \cup X_j^k \wedge e \notin X_i^k \cap X_j^k,\ k = 1,2...n\} \quad (5)$$

X_i and X_j are the positions of particle *i* and *j*. According to the equation, the distance between two particles is defined as the number of different elements between X_i and X_j.

Moreover, we propose a reset scheme to maintain the swarm diversity. In each generation, if the number of those particles sharing the same pbest, equals or exceeds a predefined number, *upper_threshold*, a reset operation is executed, in which only one of those particles is reserved, the rest are reset.

3. EXPERIMENTAL RESULT

In the experiment, the inertia weight ω decreases linearly from 0.9 to 0.5. The swarm size is 10 with *nsize* and *upper_threshold* set to 5 and 4 respectively. S-LIPS is tested on a variety of TSP instances from TSPLIB[5], comparing with S-CLPSO whose performance data are obtain from[4]. S-LIPS generate 50 results for each of the 9 TSP instances. Compiled by VC++ 2010, the programs are executed on a computer with Intel CORE 2, 2.4GHz, 2G RAM and a MS windows XP operating system.

Table 1 shows the performance of S-LIPS and S-CLPSO. S-LIPS outperforms S-CLPSO in most instances. Particularly, when the scale of the TSP instance is larger, the superiority is more evident. For all the instances with scale size over 150, the mean results of S-LIPS are better than S-CLPSO. This distinguishing feature is of special importance because TSPs of larger scale are much more challengeable than the small-scale ones for the search space complexity of a TSP is the factorial of the number of cities.

TABLE I Ccomparing S-LIPS with S-CLPSO

Instance	S-LIPS		S-CLPSO	
	Error	Deviation	Error	Deviation
kroA100	0.81%	192.94	**0.33%**	84.51
lin105	**0.40%**	54.79	0.58%	55.29
kroA150	1.69%	222.03	**1.39%**	165.36
kroA200	**0.90%**	183.80	1.21%	153.58
lin318	**1.85%**	259.56	3.54%	335.92
d493	**2.05%**	164.88	5.79%	323.53
d657	**2.97%**	331.10	5.90%	538.94
d1291	**1.78%**	342.76	3.06%	432.69
fl1577	**2.64%**	128.29	3.55%	129.08

4. CONCLUSION

In this paper, an efficient new discrete PSO based on set theory is proposed. The algorithm redefines the operators between *n*-tuples of sets and *n*-tuples of sets with possibilities as well as the concept of distance. Meanwhile, we design a reset scheme to increase the swarm diversity. The algorithm has a great improvement compared with S-CLPSO, especially in large-scale problems, which shows S-LIPS is very practical and competitive.

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