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Adequate is better: particle swarm optimization with limited-information

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ABSTRACT

Based on the interaction of individuals, particle swarm optimization (PSO) is a well-recognized algorithm to find optima in search space. In its canonical version, the trajectory of each particle is usually influenced by the best performer among its neighborhood, which thus ignores some useful information from other neighbors. To capture information of all the neighbors, the fully informed PSO is proposed, which, however, may bring redundant information into the search process. Motivated by both scenarios, here we present a particle swarm optimization with limited information, which provides each particle adequate information yet avoids the waste of information. By means of systematic analysis for the widely-used standard test functions, it is unveiled that our new algorithm outperforms both canonical PSO and fully informed PSO, especially for multimodal test functions. We further investigate the underlying mechanism from a microscopic point of view, revealing that moderate velocity, moderate diversity and best motion consensus facilitate a good balance between exploration and exploitation, which results in the good performance.

1. Introduction

As is well-known, particle swarm optimization (PSO) has been widely used as a population-based optimization algorithm [1,2], which is inspired by the animal social behaviors, such as bird flocking and fish schooling. Similar to other population-based optimization algorithms, PSO starts with the random initialization of particles in the solution space. Each particle is endowed with a random position and a random velocity at the beginning, and then adapts its search patterns based on its own experience and experiences of other individuals. Suppose the size of the population is N, the position and velocity of *ith* particle are presented as $x_i = [x_i{}^1, \ldots, x_i{}^d, \ldots, x_i{}^D] \in \mathrm{R}^D$ and $v_i = [v_i{}^1, \ldots, v_i{}^d, \ldots, v_i{}^D] \in \mathrm{R}^D$ in D-dimensional solution space. At each step, the position and velocity of particle i update according to the following equations:

$$v_i{}^d = v_i{}^d + c_1 \times r_1 \times (p_i{}^d - x_i{}^d) + c_2 \times r_2 \times (p_g{}^d - x_i{}^d) \tag{1}$$

$$x_i{}^d = x_i{}^d + v_i{}^d \tag{2}$$

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where c_1 and c_2 are two acceleration coefficients, r_1 and r_2 are two uniformly distributed random values which are independently generated in range [0, 1], $p_i = [p_i{}^1, \ldots, p_i{}^d, \ldots, p_i{}^D] \in \mathrm{R}^D$ refers to the best previous position of particle i and $p_g = [p_g{}^1, \ldots, p_g{}^d, \ldots, p_g{}^D] \in \mathrm{R}^D$ refers to the best previous position discovered by its neighbors.

The balance between global searching and local searching throughout the optimization process is critical to the performance of an optimization algorithm [3], such as the step size of the normal mutation in evolution strategies [4] and the temperature parameter in simulated annealing [5]. In order to obtain a balance between the exploration and exploitation characteristics of PSO, Shi and Eberhart [6] introduced the inertia weight coefficient and the velocity and position of each particle are updated as:

$$v_i{}^d = w \times v_i{}^d + c_1 \times r_1 \times (p_i{}^d - x_i{}^d) + c_2 \times r_2 \times (p_g{}^d - x_i{}^d) \tag{3}$$

$$x_i{}^d = x_i{}^d + v_i{}^d \tag{4}$$

where w is the inertia parameter. They found that a large w is appropriate for exploration while a small w facilitates exploitation. Trelea [7] performed a lucid analysis of a 4-parameter family of particle models and revealed that two of the parameters can be discarded without loss of generality. Further, by analyzing the convergence behavior of the PSO, Clerc and Kennedy [8] proposed a PSO variant with a constriction coefficient and derived a reasonable set of parameters. They proved that PSO with constriction coefficient is algebraically equivalent to PSO with inertia weight coefficient from a theoretical point of view. Nowadays, the PSO with constriction coefficient becomes the canonical PSO algorithm and the equations are modified as following:

$$v_i{}^d = \chi \times \left[v_i{}^d + \frac{\varphi}{2} \times r_1 \times (p_i{}^d - x_i{}^d) + \frac{\varphi}{2} \times r_2 \times (p_g{}^d - x_i{}^d) \right] \tag{5}$$

$$x_i{}^d = x_i{}^d + v_i{}^d \tag{6}$$

where χ is the constriction coefficient and is determined as: $\chi = \frac{2}{|2-\varphi-\sqrt{\varphi^2-4\varphi}|}$, $\varphi = c_1 + c_2$, $\varphi > 4$. Zhan et al. [9] proposed the adaptive PSO which can modify the coefficients in different evolutionary states. Besides, there have been a series of improvements which focus on the study of the topology structure of the swarm [10–12,17].

Obviously, in canonical PSO, the effective sources of influence are only two: each particle itself and the best performer among its neighbors. Information from the neighbor with the best performance biases the particles search in a likely promising direction. Even though information from other neighbors may lead the particle to a better region than the best neighbors, none of the information from remaining neighbors is used. Thus, important information about the solution space may be ignored through overemphasis on the single best neighbor.

In order to take full advantage of information, Mendes and Kennedy [13] proposed the fully informed particle swarm optimization (FIPSO), in which all neighbors are sources of influence. FIPSO can be depicted as follows:

$$v_i{}^d = \chi \times \left[v_i{}^d + \frac{\varphi}{K_i} \sum_{n=1}^{K_i} r_n \times (p^d_{nbr_n} - x_i{}^d) \right] \tag{7}$$

$$x_i{}^d = x_i{}^d + v_i{}^d \tag{8}$$

where K_i is the number of neighbors for particle i, and nbr_n is i's nth neighbor. $p_{nbr_n} = [p^1_{nbr_n}, \ldots, p^d_{nbr_n}, \ldots, p^D_{nbr_n}] \in \mathrm{R}^D$ is the best previous position of i's nth neighbor. Although FIPSO avoids the overemphasis on the single best neighbor and achieves a faster convergence speed than the single informed canonical PSO, each particle is given much redundant information at the same time. The redundant information weakens the influence of important information and even may mislead the particle. The indiscriminative information utilization makes FIPSO perform even worse than the canonical PSO [14].

Inspired by their works, we proposed a particle swarm optimization with limited information (LIPSO) in which only a part of its neighbors are sources of influence. For this regard, LIPSO can get rid of the overemphasis on a single neighbor and reduce the redundant information. Our results show that LIPSO outperforms canonical PSO and FIPSO especially for multimodal problems.

The rest of the paper is organized as follows. Section 2 introduces LIPSO in detail and analyzes its relationship with canonical PSO and FIPSO. Section 3 presents the performance of three PSOs and further gives some discussion about LIPSO microscopically. A summary is given in Section 4.

2. Material and methods

In this paper, we adopt the original population structure, a fully connected network that all particles are neighbors to each other. Unlike the canonical PSO that only one neighbor is a source of influence (Fig. 1(a)) and FIPSO that all neighbors are sources of influence (Fig. 1(b)), particles in LIPSO are influenced by the top W_i individuals of the population sorted by performance (each particle itself is a default member in the set) as shown in Fig. 1(c). The evolution of LIPSO can be formalized as:

$$v_i{}^d = \chi \times \left[v_i{}^d + \frac{\varphi}{W_i} \sum_{m=1}^{W_i} r_m \times (p^d_{mbr_m} - x_i{}^d) \right] \tag{9}$$

$$x_i{}^d = x_i{}^d + v_i{}^d \tag{10}$$