



Competitive and cooperative particle swarm optimization with information sharing mechanism for global optimization problems

Yuhua Li^{a,b}, Zhi-Hui Zhan^{b,c,*}, Shujin Lin^d, Jun Zhang^c, Xiaonan Luo^{a,b}

^a National Engineering Research Center of Digital Life, Guangzhou 510006, China

^b School of Information Science and Technology, Sun Yat-sen University, Guangzhou 510006, China

^c Department of Computer Science, Sun Yat-sen University, Guangzhou 510006, China

^d School of Communication and Design, Sun Yat-sen University, Guangzhou 510006, China

ARTICLE INFO

Article history:

Received 21 February 2014

Received in revised form 26 August 2014

Accepted 7 September 2014

Available online 28 September 2014

Keywords:

Particle swarm optimization (PSO)

Competition

Cooperation

Information sharing

Global optimization problems

ABSTRACT

This paper proposes an information sharing mechanism (ISM) to improve the performance of particle swarm optimization (PSO). The ISM allows each particle to share its best search information, so that all the other particles can take advantage of the shared information by communicating with it. In this way, the particles could enhance the mutual interaction with the others sufficiently and heighten their search ability greatly by using the search information of the whole swarm. Also, a competitive and cooperative (CC) operator is designed for a particle to utilize the shared information in a proper and efficient way. As the ISM share the search information among all the particles, it is an appropriate way to mix up information of the whole swarm for a better exploration of the landscape. Therefore, the competitive and cooperative PSO with ISM (CCPSO-ISM) is capable to prevent the premature convergence when solving global optimization problems. The satisfactory performance of CCPSO-ISM is evaluated by comparing it with other variants of PSOs on a set of 16 global optimization functions. Moreover, the effectiveness and efficiency of CCPSO-ISM is validated under different test environments such as biased initialization, coordinate rotated and high dimensionality.

© 2014 Elsevier Inc. All rights reserved.

1. Introduction

Inspired by the swarm behaviors of birds flocking and fish schooling, the particle swarm optimization (PSO) was first introduced by Kennedy and Eberhart in 1995 [16]. A particle in PSO uses the information of its historical best position and its neighborhood's best position to adjust its flying velocity to search for the global optimum in the solution space. However, the algorithm is not very efficient when solving complex problems because it is easy to be trapped into local optima [21,28].

The easiness of getting trapped into local optima is caused by that PSO does not sufficiently utilize its population's search information to guide the search direction. Therefore PSO has difficulty in solving complex problems [28]. The original PSO is

* Corresponding author. School of Information Science and Technology, Sun Yat-sen University, Guangzhou 510006, China.

E-mail address: zhanzh@mail.sysu.edu.cn (Z.-H. Zhan).

a global version PSO (GPSO) where all the particles are attracted by the same globally best particle and the swarm has tendency to fast converge to the current globally best point. However, as GPSO only uses the search information of the globally best particle to guide the search direction, it may be premature convergence due to the lack of diversity [22]. Therefore, GPSO is not very efficient when solving complex multimodal functions because particles cannot efficiently utilize search information of the whole swarm to find out the global optimum.

How to cope with the “attraction” phenomenon of the globally best particle in PSO and make the particles have access to more information is a critical issue in improving the performance of PSO. Kennedy and Mendes [17] introduced a local version PSO (LPSO) to handle this drawback. Particle in LPSO is influenced by its historically best position and the local neighborhood's best position. As different particles have different neighborhoods, more local best particles are used to guide the search direction. Therefore, the information used in LPSO is richer than that in GPSO. LPSO is less prone to be trapped in local optima, but usually converges more slowly [17]. However, LPSO is still not very efficient in solving complex multimodal functions because each particle still uses the information only from two exemplars, the personal best position and its neighborhood's best position. For particles have access to more search information to guide the search direction, a “fully informed particle swarm” (FIPS) is proposed in [24]. In FIPS, all the particles in the neighborhood make contributions to guide the search direction. FIPS hence uses more information from the neighbors and leads to good performance.

The performance of GPSO, LPSO and FIPS with different degrees of information sharing has indicated that the more information is efficiently utilized to guide the flying, the better performance the PSO algorithm will have. Therefore, an information sharing mechanism (ISM) is proposed in this paper to let the particles share their best search information with all the other particles, and a competitive and cooperative (CC) operator is designed to use the shared information properly and efficiently. Thus, a competitive and cooperative PSO with ISM (CCPSO-ISM) is developed to enhance the PSO performance.

The ISM is inspired by the “blackboard” idea [13]. In the ISM, a “blackboard” is used as information pool where each particle can post information, or read information. In every iteration, the particles post their historically best information to the blackboard. Any particle can access and utilize the search information provided by other particles. This way, the degree of information share is much higher than GPSO, LPSO, or FIPS. The blackboard idea is similar to the “archive” idea which has been widely used in multiobjective optimization approaches [19,43,40] to store the found nondominated solutions, and is also similar to the harmony memory strategy in harmony search algorithm [12,35]. The archive strategy and harmony memory strategy have been proven to bring better performance to optimization approaches. Therefore we can expect good performance of the blackboard strategy because it makes the search information sufficiently shared. More efficiently, the additional memory required by the blackboard idea used in this paper is almost negligible because the historically best information of each particle is stored by the particle itself. The blackboard mechanism makes all the search information shared, therefore is helpful to mix up information of the whole swarm for a better exploration of the landscape. In order to use the shared information in a proper and efficient way to improve the PSO's performance, the CC operator is designed, which is loosely inspired by the corresponding competition and cooperation behaviors in human society [6]. CCPSO-ISM is shown to have good performance by testing on global optimization problems, especially on complex multimodal functions. Moreover, it is also promising on functions with biased initialization ranges, coordinate rotation and high dimensionality.

The reminder of this paper is organized as follows. In the next section, we give a brief review of traditional PSO together with its recent developments and the previous work related to the information sharing. In Section 3, the algorithm named CCPSO-ISM is developed based on the ISM and the CC operator. Section 4 presents experimental results, comparisons and discussions. Section 5 makes further investigation on the performance of CCPSO-ISM under different environments, followed by conclusions and future work in Section 6.

2. PSO and its developments

2.1. Framework of PSO algorithm

PSO uses a swarm of particles to represent the potential solutions of the optimization problem and lets the particles fly in the search space to search for the global optimum. Assume that the particles search in a D -dimension hyperspace, a particle i has a position vector $X_i = [x_{i1}, x_{i2}, \dots, x_{iD}]$ which represents the current solution and a velocity vector $V_i = [v_{i1}, v_{i2}, \dots, v_{iD}]$ which is used to adjust the position. Moreover, each particle has a memory of a vector called the personal historically best $pBest_i$ to store the best position that the particle has found so far. The best $pBest_i$ in the particle i 's neighborhood is regarded as $nBest_i$ (for convenience, $gBest$ is used in GPSO and $lBest_i$ is used in LPSO). The velocity and position of each particle i are first initialized randomly and will be updated by the influences of its own $pBest_i$ and the corresponding $nBest_i$ as

$$v_{id} = \omega v_{id} + c_1 r_{1d} (pBest_{id} - x_{id}) + c_2 r_{2d} (nBest_{id} - x_{id}) \quad (1)$$

$$x_{id} = x_{id} + v_{id} \quad (2)$$

In Eq. (1), the velocity is updated. The ω is the inertia weight introduced by Shi and Eberhart [33] in order to balance the abilities of global search and local search; c_1 and c_2 are the acceleration coefficients which indicate the influence of the particle's historically best position and its neighborhood's best position, respectively [8]; r_{1d} and r_{2d} are two randomly generated

Download English Version:

<https://daneshyari.com/en/article/392335>

Download Persian Version:

<https://daneshyari.com/article/392335>

[Daneshyari.com](https://daneshyari.com)