Expert Systems with Applications 42 (2015) 5887–5903

Contents lists available at ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

Adaptive division of labor particle swarm optimization

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ARTICLE INFO

Article history:
Available online 6 April 2015

Keywords:
Particle swarm optimization (PSO)
Adaptive division of labor (ADOL)
Adaptive division of labor particle swarm optimization (ADOLPSO)
Convex operator
Reflectance operator

ABSTRACT

Although evident progress and considerable achievements have been attained in developing a new particle swarm optimization (PSO) algorithm, successfully balancing the exploration and exploitation capabilities of PSO to determine high-quality solutions for complex optimization problems remains a fundamental challenge. In this study, we propose a new PSO variant, namely, adaptive division of labor (ADOL) PSO (ADOLPSO), to overcome the demerits of our previous work. Specifically, an ADOL module is developed in ADOLPSO to adaptively regulate the exploration and exploitation searches of swarm. To achieve this purpose, both criteria of swarm diversity and fitness are considered during the task allocation process of the ADOLPSO current swarm. Two new operators, namely, convex operator and reflectance operator, are adopted to generate new particles from the memory swarm of ADOLPSO to further enhance the searching accuracy and convergence speed of the proposed algorithm. These two operators are activated to evolve the memory swarm only if a fitness improvement is observed in the current swarm of ADOLPSO to prevent excessive computational complexity. The proposed ADOLPSO is applied to solve 18 benchmark functions with various characteristics. Simulation results of ADOLPSO are compared with those of other nine well-established PSO variants. Experimental findings reveal that ADOLPSO significantly outperforms the other PSO variants in terms of searching accuracy, reliability, and convergence speed.

1. Introduction

Particle swarm optimization (PSO) is a swarm intelligence technique proposed by Kennedy and Eberhart (1995). This technique is inspired by the social behavior of bird flocking and fish schooling while searching for food (Banks, Vincent, & Anyakoha, 2007; del Valle, Venayagamoorthy, Mohagheghi, Hernandez, & Harley, 2008; Eberhart & Shi, 2001; Kennedy & Eberhart, 1995; Kennedy, Eberhart, & Shi, 2001). The individuals of PSO swarm are called particles, and each of them is a potential solution to optimization problems. The location of food sources represents the global optimum solution to the problem. Unlike other metaheuristic search (MS) algorithms, PSO particles can remember (1) their current position in the search space and (2) their personal best position, that is, the best position/experience that they have achieved. In other words, PSO particles roam around the search space through the current swarm while memorizing their personal best positions in the memory swarm (Clerc, 2006). While roaming in a multi-dimensional search space, the PSO swarm adopts collaboration and information-sharing strategies to guide the particles toward the global optimum solution (Banks et al., 2007; Eberhart & Shi, 2001; Kennedy & Eberhart, 1995; Kennedy et al., 2001). Given its simplistic implementation and rapid convergence to the optimal solution, PSO has been applied to various optimization problems and engineering applications (Banks, Vincent, & Anyakoha, 2008; del Valle et al., 2008; Osuna-Enciso, Cuevas, & Sossa, 2013; Sahoo, Ganguly, & Das, 2012; Zeng, Hung, Li, & Du, 2014).

Similar to other MS algorithms, PSO tends to suffer from the premature convergence issue, which is mainly caused by the rapid convergence characteristic and diversity loss of the PSO swarm during the search process. This undesirable dynamical behavior tends to trap the particles into the non-optimal region of the search space and therefore leads to low-quality solutions (Liang, Qin, Suganthan, & Baskar, 2006; van den Bergh & Engelbrecht, 2004). Proper control over the driving forces of exploration or exploitation searches is another challenging task for PSO because overemphasis on the exploration inhibits swarm convergence, whereas an excessive amount of the exploitation causes PSO swarm hastily congregate within the non-optimal region (Shi & Eberhart, 1998). Although a substantial amount of studies (Banks et al., 2007; Banks et al., 2008; del Valle et al., 2008) have been conducted to address the aforementioned drawback of PSO, most

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http://dx.doi.org/10.1016/j.eswa.2015.03.025
0957-4174/

of such variants preserve population diversity at the cost of slow convergence or complicated algorithmic structures. Alleviating the intense conflicts between the exploration/exploitation searches without significantly impairing PSO convergence speed and its simplicity of algorithmic structures remains a challenge.

Considering the probability that the best experiences of particles are distributed around the optima of the problem, Lim and Mat Isa (2013) proposed a two-layer PSO with intelligent division of labor (IDL) (TLPSO-IDL). Although TLPSO-IDL performs effectively, it has detrimental searching performance in solving problems with highly complicated fitness landscapes. The two-layer framework employed by TLPSO-IDL also tends to incur an undesirable increment in the computation costs of the algorithm. Motivated by these findings, we propose a new PSO variant, namely, adaptive division of labor (ADOL) PSO (ADOLPSO), to mitigate the demerits of TLPSO-IDL. Instead of performing task allocation on memory swarm, we design an ADOL module to adaptively allocate different searching tasks to the current swarm members of ADOLPSO. We also propose two operators, namely, convex operator and reflectance operator (CORO), to generate new particles if any fitness improvement is detected in the ADOLPSO population. The inclusion of the CORO module aims to further enhance the searching accuracy and efficiency of ADOLPSO. An elitist-based perturbation (EBP) module is also employed by ADOLPSO to resolve the premature convergence issue.

The remainder of this paper is organized as follows. Section 2 briefly discusses some related works. Section 3 elucidates the methodologies of ADOLPSO. Section 4 provides the experimental settings and simulation results. Finally, Section 5 concludes the studies conducted.

2. Related works

This section first discusses the mechanism of basic PSO (BPSO). The diverse ideas of scholars who have contributed significantly to the development of PSO variants are subsequently reviewed.

2.1. BPSO

In D-dimensional problem hyperspace, each BPSO particle is associated with two vectors to indicate its current state, that is, current position $X_i = [X_{i1}, X_{i2}, \ldots, X_{iD}]$ and velocity $V_i = [V_{i1}, V_{i2}, \ldots, V_{iD}]$. During the search process, the trajectory of each particle is stochastically adjusted in accordance with the personal best experience of particles i $P_i = [P_{i1}, P_{i2}, \ldots, P_{iD}]$ and the group best experience found by the population $P_g = [P_{g1}, P_{g2}, \ldots, P_{gD}]$ (Kennedy & Eberhart, 1995). Mathematically, dth dimensions of the velocity $V_{i,d}(t+1)$ and position $X_{i,d}(t+1)$ of particle i at $(t+1)$th iteration of the search process are updated as follows:

$$V_{i,d}(t+1) = \omega V_{i,d}(t) + c_1 r_1 (P_{i,d}(t) - X_{i,d}(t)) + c_2 r_2 (P_{g,d}(t) - X_{i,d}(t)), \tag{1}$$

$$X_{i,d}(t+1) = X_{i,d}(t) + V_{i,d}(t+1), \tag{2}$$

where $i = 1, 2, \ldots$; i is the particle index; S is the population size; c_1 and c_2 are the acceleration factors that control the influences of cognitive (i.e., P_i) and social (i.e., P_g) components, respectively; r_1 and r_2 are two random numbers with a range of [0,1]; parameter ω is called inertia weight, which is used to balance the exploration/exploitation searches of particles (Shi & Eberhart, 1998).

2.2. PSO variants and improvements

Since the introduction of PSO, extensive research has been conducted to mitigate its drawbacks. Many PSO variants have been proposed. Parameter adaptation is one of the widely used strategies to enhance the searching performance of PSO. Clerc and Kennedy (2002) incorporated a constriction factor χ into PSO to prevent swarm explosion. Ratnaweera, Halgamuge, and Watson (2004) introduced a time-varying acceleration coefficient (TVAC) strategy to dynamically vary c_1 and c_2. Two PSO-TVAC variants, namely, PSO-TVAC with mutation and self-organizing hierarchical PSO (HPSO)-TVAC (HPSO-TVAC), were proposed. Zhan, Zhang, Li, and Chung (2009) proposed an adaptive PSO (APSO) that employs an evolutionary state estimation module to identify evolutionary states and adaptively tune ω, c_1, and c_2 of the particles. Conversely, Leu and Yeh (2012) employed grey relational analysis to adjust the parameters ω, c_1, and c_2. Apart from grey relational analysis, fuzzy logic emerges as another popular tool used to dynamically adjust PSO parameters, as reported in recent literature (Melin et al., 2013; Valdez, Melin, & Castillo, 2014). By analyzing the dynamic characteristics of PSO, Zhang, Ma, Wei, and Liang (2014) concluded that engineering experience can be used to determine the parameters of PSO. The researchers proposed a novel parameter strategy for PSO based on the concepts of overshoot and the peak time of a transition process. Yang, Gao, Liu, and Song (2015) proposed a high-order $(1/\pi^2)$ function to non-linearly vary the parameter ω because their experimental studies revealed that the performance of PSO is more sensitive to large variations of ω than those of c_1 and c_2. On the contrary, Zhang, Tang, Hua, and Guan (2015) employed Bayesian technique to finetune the parameter ω of each particle on the basis of its previous positions. Ardizzon, Cavazzini, and Pavesi (2015) advocated a novel approach in performing particle task differentiation. Two types of particles called "explorer" and "settler" were categorized. Their respective parameters ω, c_1, and c_2, were adjusted on the basis of their respective distance from the best solution in swarm. Unlike most parameter adaptation strategies that attempt to modify the parameters ω, c_1, and c_2, a cautious PSO with conditional random was proposed by Chan and Chen (2015) to adjust the weight of the personal and global best positions of particles through a prescribed probability and a random value.

Population topology emerges as another key factor that influences the performance of PSO because it controls the information flow rate of the best solution within swarm (Kennedy, 1999; Kennedy & Mendes, 2002). Kathrada (2009) proposed a flexible PSO (FlexiPSO) by combining the global and local versions of PSO on the basis of acceleration coefficient heuristic. Similarly, Beheshti and Shamsuddin (2015) combined both global and local topologies into their proposed non-parametric PSO. Two quadratic interpolation operators were also included in their work to enhance the search capability of the algorithm. Mendes, Kennedy, and Neves (2004) proposed a fully informed PSO (FIPSO) by acknowledging the importance of neighborhood members in influencing the movement of a particle. To address the inferior performance of FIPSO in multi-modal problems, Qu, Suganthan, and Das (2013) developed a distance-based locally informed PSO (LIPS). LIPS utilizes the local information contributed by the nearest distance-based neighborhood of a particle to form different stable niches. Matsushita (2012) proposed an independent-minded PSO (IPSO) and an improved IPSO (IIPSO) with a dynamic topology. IPSO and IIPSO particles can stochastically decide whether a particle is affected by swarm or it acts with self-reliance at individual and dimensional levels, respectively. Liang and Suganthan (2005) proposed a dynamic multi-swarm PSO (DMS-PSO) with a dynamically changing neighborhood structure. To overcome the poor exploitation capability of DMS-PSO, Xu, Tang, Li, Hua, and Guan (2015) incorporated a cooperative learning (CL) strategy into their DMS-PSO-CL to ensure highly effective information exchanges between the worst and best particles across