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Particle swarm optimization with dual-level task allocation

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ABSTRACT

Particle swarm optimization (PSO) is a well-known algorithm for global optimization over continuous search spaces. However, this algorithm is limited by the intense conflict between exploration and exploitation search processes. This improper adjustment of exploration and exploitation search processes can introduce an inappropriate level of diversity into the swarm, thereby either decelerating the convergence rate of the algorithm (caused by the excessive diversity) or inducing premature convergence (as a result of insufficient diversity). To address this issue, we propose a new PSO variant, namely, the PSO with dual-level task allocation (PSO–DLTA). Two task allocation modules, that is, the dimension-level task allocation (DTA) and the individual-level task allocation (ITA) modules, are developed in PSO–DLTA to balance the exploration and exploitation search processes. Unlike existing population-based and individual-based task allocation approaches, the DTA module assigns different search strategies to different dimensional components of a particle. Meanwhile, the ITA module serves as an alternative learning phase to enhance the PSO–DLTA particle if it fails to improve in terms of fitness in the DTA module. To demonstrate the effectiveness and efficiency of PSO–DLTA, we compare it with several recently developed optimization algorithms on 25 benchmark and 2 engineering design problems. Experimental results reveal that the proposed PSO–DLTA is more competitive than its contenders in terms of searching accuracy, reliability, and efficiency with respect to most of the tested functions.

1. Introduction

Kennedy and Eberhart (1995) proposed particle swarm optimization (PSO), which is a population-based metaheuristic search (MS) algorithm. This algorithm is inspired by the collective and collaborative behaviors of birds and fish (i.e., flocking and schooling) when scavenging for food. As a population-based optimization technique, PSO searches a solution space using a pool of individuals. The position of each individual (i.e., particle) represents a potential solution, which is a point in the search space. Meanwhile, the global optimum is regarded as the location of the food (Liang et al., 2006). The PSO particles also collaborate and share information with one another as they navigate through the search space of a multidimensional problem independently and stochastically. This mechanism enables the PSO population to move gradually toward the promising regions from different directions, thereby resulting in swarm convergence (Banks et al., 2007; Eberhart and Shi, 2001). PSO has gained significant attention in the research area of computational intelligence because of its competitive performance, despite its simple implementation. Moreover, it has been applied to solve many real-world engineering design problems, such as power system design (AlRashidi and El-Hawary, 2009; Chen et al., 2007; del Valle et al., 2008; Neyestani et al., 2010; Wang et al., 2013), artificial neural network training (Mirjalili et al., 2012; Yaghini et al., 2013), data clustering (Kiranyaz et al., 2010; Shih, 2006; Sun et al., 2012; Yang et al., 2009), data mining (Özbakır and Delice, 2011; Sarath and Ravi, 2013; Wang et al., 2007), and parameter estimation and system identification (Liu et al., 2008; Modares et al., 2010; Sakthivel et al., 2010), as well as many other engineering problems (Alia and Mandava, 2011; Huang et al., 2009; Lin et al., 2009; Paoli et al., 2009; Sharma et al., 2009).

Despite its promising performance, PSO is limited by the intense conflict between exploration and exploitation search processes (Li et al., 2012; Wang et al., 2011). These two strategies exhibit contradictory searching behaviors as the main features of MS algorithms. Exploration search process encourages the algorithm to wander around the entire search space to cover unvisited regions, whereas exploitation search process focuses on the local refinement of the already-determined near-optimal solutions. In practice, these two aspects must be well-balanced and neither should be overemphasized because excessive exploration causes PSO to consume increased amounts of computation resources (i.e., fitness evaluations) in locating

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promising regions, whereas excessive exploitation tends to depress swarm diversity (Chen et al., 2009). Another undesirable dynamic behavior exhibited by the basic version of PSO is known as premature convergence (van den Bergh and Engelbrecht, 2004). This behavior is induced by the rapid convergence characteristic of PSO, which results in the tendency of swarms to converge prematurely in the best position as determined at a point in the early stage of optimization. These positions are typically denote the local optimum, which may be distant from the actual global optimum. In addition, such positions could mislead the PSO swarm. Once the swarm is deceived and has congregated in these areas, the opportunity to explore other possible solutions is limited for the population. Thus, the PSO swarm is trapped in the local optima of the search space, and poor optimization solutions are generated.

To address the aforementioned drawbacks, researchers have conducted many studies and introduced various approaches to improve PSO searching performance (Banks et al., 2007, 2008; Beheshti et al., 2013; del Valle et al., 2008; Li et al., 2012; Marinakis and Marinaki, 2013; Montes de Oca et al., 2011; Zhan et al., 2011). Nevertheless, the majority of existing PSO variants tend to restrict either the population or an individual particle to perform one type of searching mechanism (i.e., either exploration or exploitation search process). For example, all particles in the Frankenstein PSO (FPSO) (Montes de Oca et al., 2009b) exhibit exploitative behavior in the early stage of optimization because the FPSO population is initialized with fully connected topology. The topology connectivity of FPSO decreases over time with search progress, and the searching behavior of the population becomes increasingly explorative. Meanwhile, the self-learning PSO (SLPSO) proposed by Li et al. (2012) employs an adaptive learning framework that enables a particle to choose one of four searching strategies (i.e., exploration, exploitation, convergence, and jumping out) based on the location of the particle in the subregion of the search space. Once the searching strategy of each SLPSO particle has been determined, the corresponding particle must apply the selected strategy in all dimensional components. As with SLPSO, the heterogeneity concept employed by heterogeneous PSO (HPSO) (Montes de Oca et al., 2009a) is restricted on the individual level given that all dimensional components in the position vector of a particular HPSO particle are influenced by either a constant neighborhood size, model of influence, update rule, or parameter values.

Based on these observations, most existing PSO variants allocate tasks (e.g., the task of determining search strategies) at the population and individual levels. These population- and individual-level task allocation (ITA) approaches may improve algorithm performance. However, studies on the feasibility of PSO for task allocation at the dimension level is limited (i.e., assigning different searching mechanisms to each particle in different dimensional components of the search space). A recent study (Jin et al., 2013) revealed that each particle in the swarm should select different search tasks for different dimensional components based on its own characteristic. In the light of this finding, we propose a new variant of PSO, namely, the PSO with dual-level task allocation (PSO–DLTA). The proposed PSO–DLTA is an innovative framework that consists of two types of task allocation modules, that is, the dimension-level task allocation (DTA) and individual-level task allocation (ITA) modules. Specifically, the DTA module attempts to assign different searching mechanisms to the different dimensional components of a particle based on the distance between the aforementioned particle and the global best particle in each dimensional component. Given that DTA module is not guaranteed to always produce improved solutions, we employ ITA module as an alternative learning phase to evolve further the particles that fail to improve in terms of fitness in the previous DTA phase. Unlike in the DTA module, all of the dimensional components of the involved particle apply the same searching mechanism in the ITA module.

The remainder of the current paper is organized as follows. Section 2 briefly presents some related works. Section 3 describes the methodologies of PSO–DLTA in detail. Sections 4–6 tabulate and discuss the experimental settings and simulation results. Finally, Section 7 concludes the work.

2. Related works

This section begins with a brief description of basic PSO (BPSO). Subsequently, several state-of-the-art PSO variants are reviewed comprehensively.

2.1. BPSO

The BPSO swarm is modeled as a group of particles with negligible mass and volume. These particles navigate through the D dimensional hyperspace. Each particle represents the potential solution of a given problem, and it is associated with two vectors, namely, the position vector $X_i=[X_{i1}, X_{i2},\ldots,X_{iD}]$ and the velocity vector $V_i=[V_{i1}, V_{i2},\ldots,V_{iD}]$. Each particle i can memorize its best experience, which is represented by the personal best position $P_i=[P_{i1}, P_{i2},\ldots,P_{iD}]$. During the searching process, the trajectory of each particle i in the population is dynamically adjusted according to the personal best experience P_i of particle i and the group best experience in the neighborhood of particle i, that is, $P_n=[P_{n1}, P_{n2},\ldots,P_{nD}]$ (Eberhart and Shi, 2001; Kennedy and Eberhart, 1995). In the literature, P_n is denoted as P_g and P_l, which represent the global and local versions of PSO, respectively (Kennedy, 1999; Kennedy and Mendes, 2002). In global PSO, a particle uses the best historical experience of the entire swarm as its neighborhood's best position. In local PSO, a particle uses the best historical experience of the particle in its neighborhood, which is defined by topological structures such as ring, pyramid, or von Neumann structures (Kennedy, 1999; Kennedy and Mendes, 2002). Mathematically, the d-th dimension of the velocity of particle i $V_{i,d}(t+1)$ and the position $X_{i,d}(t+1)$ are updated as follows at the $(t+1)$th iteration of the searching process:

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

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

where $i=1, 2,\ldots,S$ is the index of the particle; S is the population size; c_1 and c_2 are the acceleration coefficients that control the influences of cognitive (i.e., P_i) and social (i.e., P_n) components, respectively; r_1 and r_2 are two random numbers that are generated from a uniform distribution with a range of [0, 1]; and ω is the inertia weight that is employed to balance the exploration and exploitation search processes of particles (Shi and Eberhart, 1998).

2.2. PSO variants and improvements

Since the introduction of PSO, it has remained the preferred choice of researchers in the area of computational intelligence. Scholars have proposed diverse ideas that contribute significantly to the development of new PSO variants.

The first area of research concentrates on the PSO parameter adaptation strategy. Ratnaweera et al. (2004) proposed a time-varying acceleration coefficient strategy wherein c_1 and c_2 change dynamically over time to improve the regulation of the exploration and exploitation search processes. Unlike Ratnaweera et al. (2004), Juang et al. (2011) proposed adaptive fuzzy PSO, which adaptively adjusts c_1 and c_2 according to fuzzy set theory. Zhan et al. (2009) introduced the evolutionary states estimation (ESE) module into their adaptive PSO (APSO) to identify the evolutionary states. The output of the ESE module is then used to adapt the ω,