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A cooperative particle swarm optimizer with stochastic movements for computationally expensive numerical optimization problems

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ABSTRACT

Nature is the rich principal source for developing optimization algorithms. Metaheuristic algorithms can be classified with the emphasis on the source of inspiration into several categories such as biology, physics, and chemistry. The particle swarm optimization (PSO) is one of the most well-known bio-inspired optimization algorithms which mimics movement behavior of animal flocks especially bird and fish flocking. In standard PSO, velocity of each particle is influenced by the best individual and its best personal experience. This approach could make particles trap into the local optimums and miss opportunities of jumping to far better optimums than the currents and sometimes causes fast premature convergence. To overcome this issue, a new movement concept, so called extraordinariness particle swarm optimizer (EPSO) is proposed in this paper. The main contribution of this study is proposing extraordinary motion for particles in the PSO. Indeed, unlike predefined movement used in the PSO, particles in the EPSO can move toward a target which can be global best, local bests, or even the worst individual. The proposed improved PSO outperforms than the standard PSO and its variants for benchmarks such as CEC 2015 benchmarks. In addition, several constrained and engineering design problems have been tackled using the improved PSO and the optimization results have been compared with the standard PSO, variants of PSO, and other optimizers.

1. Introduction

Nowadays, most of new algorithms have been developed by drawing inspiration from nature, so called nature-inspired algorithms [1]. Those algorithms are well suited to solve complex computational problems in both designing and operation optimization problems. There is a fact that existing algorithms could handle number of optimization problems in different areas, however no specific algorithm could solve well for all problems and some algorithms are more efficiently applied for some problems than the others [2].

Metaheuristic optimization algorithms are inspired by natural systems emphasizing into three main sources including biology, physics, and chemistry. Bio-inspired algorithms are based on successful characteristics of biological systems and natural phenomena such as the genetic algorithms (GAs) [3], the ant system [4], the particle swarm optimization (PSO) [5].

The other heuristic optimization algorithms inspired by physical phenomena have been widely applied in high dimension optimization problems. The good examples are the simulated annealing (SA) [6], the central force optimization [7], the harmony search algorithm (HS) [8], the gravitation search algorithm (GSA) [9], and the water cycle algorithm [10]. The metaheuristic algorithms have been widely applied for solving optimization problems in many fields such as mathematics [11], heat transfer [12], engineering design [13–17], and so forth.

Among those algorithms, the PSO is one of the most common optimizer applied for various problems arising in sciences and engineering. The PSO is a metaheuristic global optimization technique originally developed by Kennedy and Eberhart [5] inspired by the movement behavior of bird and fish flock. The PSO mimics the society of animals (i.e., bird or fish) in which each individual has interaction with others and also with their environment.

An individual in the PSO so called a particle tends to move toward the best particle among them (global best, *gbest*) also with considering their best experience (personal best, *pbest*). The PSO tries to balance exploration and exploitation processes by combining local and global searches. Talking about advantages of PSO, fast convergence, easy implementation, and simple computation are

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considered as its advantages. In the other hand, the PSO exhibits some drawbacks such as trapping in local optima and slow convergence rate in the later iterations when particles are in adjacent area of optimal solution.

Several variants of PSO are proposed to overcome mentioned disadvantages. Some researchers proposed an improved PSO by moving particles in a quantum space and establishing a quantum delta potential model [18–20]. Number of approaches tackled the premature convergence by modifying swarm population such as initializing the population using nonlinear simplex method [21], partitioning the population into several sub-population to ensure information exchanging in the entire population [22], or using Gaussian mutation [23].

There are few parameters in the standard PSO that give potential advantage to enhance performance of an algorithm. Among user parameters of PSO, several strategies of inertia weight adjusting methods are proposed categorizing into three main groups: constant inertia weight [24], time-varying inertia weight [25–27], and adaptive inertia weight [28–30].

In this paper, a new approach is proposed to the standard PSO focusing on movement of particles. Instead of the two coefficients presenting cognitive and social components, a combined operator is used. The information sharing among the personal best, global best, and other particles is stochastically determined.

Particles in the new movement strategy can exchange information with any other particles such as global best, local bests, or even the worst particle. This approach may help the PSO to escape from the local optima, as particles always do not move toward their best locations. In the other word, particles may not fly toward its best and global best and may break the swarm rule used in the standard PSO and become extraordinary particles. Also, for the mutation part in the improved PSO, unlike the standard PSO which is using the inertia weight (w), the uniform random search also is utilized.

The reminding of this paper is organized as follows: Section 2 describes the standards PSO. The proposed extraordinary particle swarm optimization (EPSO) is presented in Section 3. In Section 4, the EPSO along with other optimizers have been applied to a number of unconstrained and constrained benchmarks (e.g., CEC 2015 benchmarks and engineering design problems) and statistical optimization results have been provided. Finally, this paper ends up with the conclusions section.

2. Particle swarm optimization

The PSO is a population-based optimizer inspired by collective behavior of animal flocking. This algorithm is originally developed by Eberhart and Kennedy [5] and has been widely applied to many fields in optimization and computational intelligence. As other evolutionary algorithms, the PSO initializes a system of random solutions and evolves optima through successive generations.

The potential solutions in the PSO so called particles fly through the search space following the current best individuals. Each particle in the PSO at iteration t is characterized by its location and velocity. All particles is evaluated by fitness function via its location and oriented by velocity vector [31].

The PSO starts with an initial group of random particles in the D-dimensional search space of the problem. The particle ith at iteration t is represented by position $X_i^t = \left(x_i^2, x_i^2, \cdots, x_i^D\right)$ and velocity $V_i^t = \left(v_i^2, v_i^2, \cdots, v_i^D\right)$. At every iteration, location of each particle is updated by moving toward the two best locations (i.e., global and personal bests) as given in the following equation [25]:

$$\vec{V}_i(t+1) = w(t)\vec{V}_i(t) + r_1C_1\left(p\vec{best}_i(t) - \vec{X}_i(t)\right) + r_2C_2\left(g\vec{best}(t) - \vec{X}_i(t)\right) \quad (1)$$

$$\vec{X}_i(t+1) = \vec{X}_i(t) + \vec{V}_i(t+1) \quad (2)$$

where r_1 and r_2 are uniform distributed random numbers in [0,1], C_1 and C_2 are cognitive and social coefficients known as acceleration constants, respectively; $pbest_i(t)$ denotes the best personal position of the particle ith and $gbest$ is the best position among all particles at iteration t; $w(t)$ is an inertia weight, a user parameter between zero to one. The velocity of each particle is limited by the range of $\left[v_{\min}^D, v_{\max}^D\right]$. In entire paper, notations having vector sign correspond vector values, otherwise the rest of notations and parameters are considered as scalar values.

3. Extraordinary particle swarm optimization (EPSO)

In the standard PSO, balance of exploitation and exploration is obtained by combining local and global searches as can be seen in Eq. (1). Shi and Eberhart [25] stated that the inertia weight represents exploitation–exploration tradeoff. It means larger inertia weight is preferred for global search. However, in some situations for multimodal problems such as Rastrigin and Griewank functions, this factor cannot successfully apply [32].

As mentioned in Section 2, the PSO simulates movement behaviors of animal flocking when searching food. Among particles, there is an information sharing mechanism that makes all particles move following the current optimum particles. Although, this process represents some advantages, however, there are several drawbacks in terms of being trapped in local optima and fast immature convergence rate.

Despite moving toward the global best enhances convergence, however, there is a high chance for this approach to easily fall into local optima. Directions offered by combination of global and personal bests may not be always the fastest and efficient directions to obtain global optimum. In fact, sometimes moving toward worst particles may be considered as the fastest way to reach the global optimum solution. That motivates a new strategy which can speed up the mature convergence and give great potential to escape from local optima (similar to the SA for accepting worst solutions).

In the EPSO, in addition of moving toward global and personal bests, particles may fly to their determined target. Each particle has its own target at every iteration. The target could be the global best, personal best or any particle with different cost/fitness. Particles choose their target stochastically and change their targets through iterations. The particles in the EPSO may not follow the current bests (i.e., personal and global bests) and tend to interrupt the movement rules used in the standard PSO. That is the reason we call them as extraordinary particles. At every iteration, each extraordinary particle randomly chooses its own target to move toward. The updating equations for the particle velocity and its new location are given as follows:

$$\vec{V}_i(t+1) = C\left(\vec{X}_{Ti}(t) - \vec{X}_i(t)\right) \quad (3)$$

$$\vec{X}_i(t+1) = \vec{X}_i(t) + \vec{V}_i(t+1) \quad (4)$$

where $X_{Ti}(t)$ is the determined target T of particle ith at iteration t; C is combined component including cognitive and social factors. The target particle could be the best among entire particles or the best that extraordinary particle has experienced or just an average or even worst particle in the swarm population.

Generally, combined coefficient C can express both cognitive and social coefficients depending on the target of extraordinary particle at every iteration. For instance, if the chosen target is global or personal bests, C coefficient, therefore is cognitive or social coefficient.

Uniform random search process is also taken part in the EPSO using the range of potential target from 0 to T_{up} where it is the upper bound of target range. A user-defined parameter so called α