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A multi-swarm cooperative multistage perturbation guiding particle swarm optimizer

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ABSTRACT

Inspired by the ideas of multi-swarm information sharing and elitist perturbation guiding a novel multi-swarm cooperative multistage perturbation guiding particle swarm optimizer (MCpPSO) is proposed in this paper. The multi-swarm information sharing idea is to harmoniously improve the evolving efficiency via information communicating and sharing among different sub-swarms with different evolution mechanisms. It is possible to drive a stagnated sub-swarm to revitalize once again with the beneficial information obtained from other sub-swarms. Multistage elitist perturbation guiding strategy aims to slow down the learning speed and intensity in a certain extent from the global best individual while keeping the elitist learning mechanism. It effectively enlarges the exploration domain and diversifies the flying tracks of particles. Extensive experiments indicate that the proposed strategies are necessary and cooperative, both of which construct a promising algorithm MCpPSO when comparing with other particle swarm optimizers and state-of-the-art algorithms. The ideas of central position perturbation along the global best particle, different computing approaches for central position and important parameters influence analysis are presented and analyzed.

1. Introduction

Particle swarm optimization (PSO) [12,31] is a population-based stochastic search technique for solving optimization problems. It has been proven to be efficient and effective for various applications in scientific and engineering domains. It is inspired by the regularity of birds clustering activities, using the organizational social behaviors to replace the natural selection mechanism of evolutionary algorithm [5]. Each particle has the abilities of "individual cognition" and "social cognition". PSO manages to search the optimal solutions by the cooperations of particles in the swarm. Since PSO is simple, easy to realize and has few parameters, it has gained increasing popularity among researchers and practitioners as a robust and efficient technique for solving complex and difficult optimization problems [1,10,18,20,22,32]. Furthermore, many other evolutionary optimization algorithms emerge and attract extensive attentions, such as differential evolution [4,29,36], real-coded genetic/memetic algorithms [6,21,23], artificial bee colony [9,14].

The flying velocity of each particle is modified iteratively by its personal best position and the best position found by the entire swarm. As a result, each particle searches around a region defined by its personal best position and the position of the population best [13]. That is, PSO is somewhat arbitrary to make all the particles get acquainted with the same "social cognition" from the best position (gbest). In this condition, no matter how far the particle is from the gbest, every particle learns information from the same source, i.e., gbest. As a result, all of them are quickly attracted to the optimal position, and the swarm diversity is decreasing very fast. Therefore, avoiding being trapped by local optima while accelerating convergence speed has become a most important and appealing goal in PSO research [28].

As PSO is simple in concept and effective to explore global solutions for various optimization problems, it has become more and more important and has been one of the most popular optimization techniques. Mendes et al. [19] think that each individual of PSO is not simply influenced by the best performer among his neighbors and they decided to make the individuals "fully informed". Li [15] proposed a simple yet effective niching particle swarm optimization algorithm, which uses a ring neighborhood topology and does not require any niching parameters. It evolves by using individual particles' local memories to form a stable network retaining the best positions found so far, while these particles explore the

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search space more broadly. Liang et al. [16] proposed a novel learning strategy whereby all other particles' historical best information is used to update a particle's velocity. This strategy enables the diversity of the swarm to be preserved to discourage premature convergence and achieves very competitive performance for multimodal functions. Perturbed particle swarm algorithm [37] is based on a concept of particles update strategy with possibility. Perturbing the global optimal particle in a certain range, the population diversity is somewhat increased while remaining the elitist leaning mechanism of PSO. Nickabadi et al. [25] proposed a new adaptive inertia weight by using the success rate of the swarm as its feedback parameter to ascertain the particles' situation in the search space. Zhan et al. [35] proposed an orthogonal learning (OL) strategy for PSO to discover more useful information that lies in the above two experiences via orthogonal experimental design. The appropriate adaptive or self-adaptive learning mechanism [33,30,8,11] are the most important strategies to keep the well balance between global exploration and local exploitation. Multi-swarm cooperative particle swarm optimization [26] is a multiple swarm-based improved algorithm with center communication. This algorithm divides the whole search space into local subspaces, and different sub-swarms communicate and share exploitation information each other, reducing the possibility of getting into the local optimum. Neri et al. [24] proposed a novel compact particle swarm optimization (cPSO). It does not use a swarm of particles and does not store neither the positions nor the velocities. On the contrary, cPSO employs a probabilistic representation of the swarm's behavior. Based on the observations that a particle surfing on sine waves in nature and a particle seeking an optimal location attempted to catch another wave randomly, manipulating its frequency and amplitude, Pehlivanoglu [27] proposed a periodic mutation operation and a multifrequency vibrational PSO. Chen et al. [3] transplanted the aging mechanism to particle swarm optimization and proposed a PSO with an aging leader and challengers. It is characterized by assigning the leader of the swarm with a growing age and a lifespan, and allowing the other individuals to challenge the leadership when the leader becomes aged. Zhao et al. [38] proposed a new PSO searching mechanism based on principal component analysis (PCA) and line search (LS), in which PCA is mainly used to efficiently mine population information for the promising principal component directions and then LS strategy is utilized on them. In order to overcome the suffers of the premature convergence, Campos et al. [2] proposed a variant of PSO, bare bones particle swarm optimization with scale matrix adaptation (SMA-BBPSO). In the SMA-BBPSO, the position of a particle is selected from a multivariate t-distribution with a rule for adaptation of its scale matrix.

Inspired by the ideas of multi-swarm information sharing and elitist perturbation guiding, this paper presents a novel multi-swarm cooperative multistage perturbation guiding particle swarm optimizer (MCpPSO) with multi-swarm information sharing mechanism and multistage global perturbation guiding strategy. In this algorithm, the flying velocity is updated with a different manner from the traditional PSO. Each particle updates itself by its own experience, the optimal position of its sub-swarm, and the information coming from other sub-swarms. During the evolution, the diversity is also increased a little by a perturbation operation around the global optimal solution. Two main strategies increase the possibilities of jumping out of local optima, and make the particles approach to the global optimal solution as near as possible. So the comprehensive performance of the algorithm is possible to be improved greatly. Furthermore, the synchronous perturbation operation of central position along the global best particle, different computing models for central position and important parameters influence analysis are also presented.

The rest of this paper is organized as follows. The related algorithms and foundations are introduced in Section 2. The proposed algorithm MCpPSO is detailed described in Section 3. The comprehensive experimental comparisons and algorithmic analysis on MCpPSO are presented in Section 4. The questions on the central position perturbation along the global best particle, different computing approaches for central position and important parameters influence analysis are analyzed in Section 5. The overall conclusion and the possible future research are given in Section 6.

2. PSO and related topics

2.1. Particle swarm optimization algorithm

PSO [12,31] executes its search in the definition domain through the accumulating velocity and position information. Each particle enhances itself by keeping its track learning from two "optimal solutions" in PSO population: one is the optimal solution found by itself and the other is the optimal solution found by the particle swarm.

A standard particle swarm optimizer maintains a swarm of particles and each individual is composed of three D-dimensional vectors, where D is the dimensionality of the search space. These are the current position x_i, the previous best position p_i, and the velocity v_i. The current position $x_i = (x_{i,1}, \ldots, x_{i,D})$ can be considered as a set of coordinates describing a point in the space. The best solution found so far is stored in $p_i = (p_{i,1}, \ldots, p_{i,D})$. New positions are obtained by adding $v_i = (v_{i,1}, \ldots, v_{i,D})$ coordinates to x_i, and the algorithm aims at a new promising position by adjusting v_i, which can be seen as a step size as the usual optimization algorithm.

In essence, the trajectory of each particle is updated according to its own flying experience as well as to that of the best particle in the swarm. The velocity and position updating equations are given as Eqs. (1) and (2).

$$v_{i,d}^{k+1} = \omega v_{i,d}^{k} + c_1 r_1^k (p_{i,d}^k - x_{i,d}^k) + c_2 r_2^k (p_{g,d}^k - x_{i,d}^k) \quad (1)$$

$$x_{i,d}^{k+1} = x_{i,d}^{k} + v_{i,d}^{k+1} \quad (2)$$

where $v_{i,d}^k$ is the dth dimension velocity of particle i in cycle k; $x_{i,d}^k$ is the dth dimension position of particle i in cycle k; $p_{i,d}^k$ is the dth dimension of personal best (pbest) of particle i in cycle k; $p_{g,d}^k$ is the dth dimension of the gbest in cycle k; ω is the inertia weight; c_1 is the cognitive weight and c_2 is the social weight; and r_1 and r_2 are two random values uniformly distributed in the range of [0, 1]. Experimental results suggest that it is preferable to initialize the inertia weight to a large value, giving the priority to global exploration of the search space, and gradually decreasing so as to obtain refined solutions.

2.2. Multi-swarm evolution based on central information exchange

PSO is easy to be trapped by evolution stagnation if population size is too small. However, the overlarge population size will affect the converging speed of algorithm. So it is difficult to decide the population size for different questions. Based on these observations, the large swarm is divided into several sub-swarms with independent evolution in this paper. On one hand, particles independently search for even better solutions as traditional PSOs. On the other hand, they also acquire information from the other sub-swarms [26], which are independently evolving and have distinctive evolution information from each other. The evolution information is then sent to other sub-swarms and to guide the search of all the particles. The information sharing mechanism of this paper is implemented with the central position, which is the