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A decentralized quantum-inspired particle swarm optimization algorithm with cellular structured population

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ABSTRACT

This paper proposes a decentralized form of quantum-inspired particle swarm optimization (QPSO) with cellular structured population (called cQPSO) for keeping the population diversity and balancing the global and local search. The cQPSO is further improved by re-designing the local attractor in the sub-population (called cQPSO-*lbest*) in order to accelerate the diffusion of the best solution and thus enhance the performance of cQPSO. The particles in cQPSO and cQPSO-*lbest* are distributed in a two-dimensional (2D) grid and only allowed to interact with their neighbors according to the specified neighborhood, which plays a role in exploiting the search space inside the neighborhood. The overlapping particles work for delivering the information among the nearest neighborhoods acting as exploring the search space with diffusion of solutions during the evolutionary process. Theoretical studies are made to analyze the global convergence of cPSO and cQPSO-*lbest* based on the theory of probabilistic metric space. We systematically investigate the performance of cQPSO-*lbest* on 42 benchmark functions with different properties (including unimodal, multimodal, separated, shifted, rotated, noisy, and mis-scaled) and compare with a set of PSO variants with different topologies and swarm-based evolutionary algorithms (EAs). The experimental results demonstrate the better performance of cQPSO-*lbest*. Moreover, two real-world problems, which are two-dimensional (2D) IIR digital filter design and economic dispatch (ED) problem from power systems area, are used to evaluate cQPSO-*lbest* and the experimental results verified the advantages of cQPSO-*lbest*.

1. Introduction

Particle swarm optimization (PSO) is a population-based random search optimization technique, which was originally proposed by Kennedy and Eberhart [23,55] and it is an important research branch of swarm intelligence (SI). PSO is inspired by the metaphor of social interaction and communication, such as bird flocking, fish schooling, and swarm insects searching for food.

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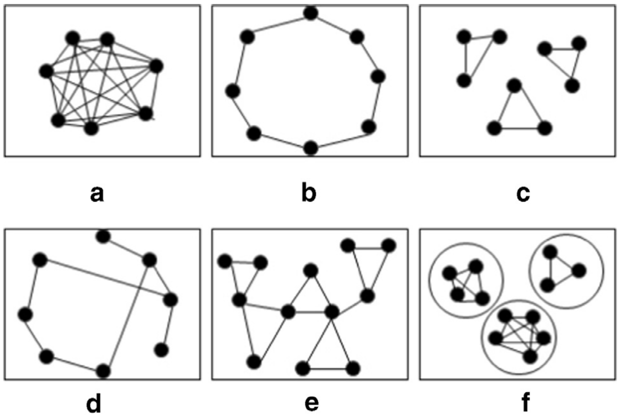

Fig. 1. Different neighborhood topologies of particles (black points) in PSO (a) *gbest* topology; (b) *lbest* topology; (c) multi-swarm topology; (d) sociometric topology with two "small-world" shortcuts (e) FIPS topology; (f) multi-species sub-population topology.

PSO also contains the concept of evolution as that in evolutionary algorithms (EAs), but it does not need evolution operators, such as selection and crossover. In PSO, each particle in the population is regarded as a candidate solution and represented by two vectors, namely the position vector and the velocity vector. Each particle flies in a given multidimensional continuous search space and under the guidance of its previous best position and the global best position. PSO optimizes the problems through the iterative process with respect to the objective function. Since it is easy to implement with few parameters to be adjusted yet with inexpensive computational workload, PSO has been widely used in many research and application areas [47].

As the other EAs, PSO may also be trapped in the local minimum especially when solving the complex high dimensional problems. This leads to premature convergence and great performance loss of PSO. Researchers have proposed many methods to improve the performance of PSO from several aspects. In the PSO with inertia weight (PSO-In) [55] and the PSO with constriction factor (PSO-Co) [15], all the particles are neighbors of each other and the neighborhood topology is known as global best topology or the global best model, which is shown in Fig. 1(a). Once the global best particle falls into the local minimum area, all the other particles will be misled by the global best particle to the area. Therefore, some researchers have investigated other swarm neighborhood topologies [9,20,24,26,30,32,38,39,43,44,57,65,69]. In the *lbest* neighborhood topology, which is shown in Fig. 1(b) [24], each particle is influenced by its two adjacent neighbors. A dynamic multi-swarm PSO (DMS-PSO) algorithm was proposed in [39] with the whole population divided into many small swarms and regrouped frequently. Kennedy studied the different sociometric topologies for the swarm population with small-worlds like the social network [20]. Fig. 1(e) is an example of the sociometric topology with two "small-world" shortcuts. Later Kennedy and Mendes proposed the fully-informed neighborhood topology in [25] as depicted in Fig. 1(e). In [32], the swarm population is divided into multi-species sub-populations according to the similarity to solve the multi-modal functions. The topology is shown in Fig. 1(f).

As the particle trajectories in PSO are semi-deterministic defined by the velocity update equation with two uniformly distributed random acceleration coefficients, the search space of each particle at each iteration is restricted and the global search ability of the algorithm may be weakened especially in the later stage of search process. Researchers have proposed different ways to simulate the particle trajectories, such as direct sampling, using a random number generator, or from a distribution of practical interests [21,22,27–29,34,50,52,60,64]. Among different EAs, each algorithm has its own advantage which is different from other algorithms. Therefore PSO incorporating other search methods or evolutionary operators in other EAs has also been widely studied by many researchers [3,6,13,14,16,16,40,53,68,77]. The adaptive learning strategies for the particles along with the search process in PSO were proposed in order to make the swarm work more intelligent [18,19,31,56,70,76]. The niching and clustering techniques were designed in PSO to solve the multimodal and dynamic problems [33,49,73,75]. Li et al. proposed the cooperative co-evolutionary PSO algorithms to solve the large-scale optimization problems [35,45]. In [36], the competitive and cooperative operator with information sharing mechanism is proposed in PSO algorithm in order to prevent the premature convergence. The discrete versions of PSO algorithm are also studied by the researchers for solving the binary or discrete problems [5,46,54].

According to the trajectory analysis of particles in PSO by Clerc and Kennedy [10], we proposed that the position of particle in PSO is sampled by the quantum δ potential well model around the mean best position [60,62,66],and the resulting algorithm is quantum-inspired particle swarm optimization (QPSO). The particles in QPSO have no velocity vector, which is quite different from PSO, and QPSO has fewer parameters to adjust than PSO, making it much easier to tune. QPSO has attracted much attention as a probabilistic variant of PSO for solving many optimization problems with satisfying performance. As other SI algorithms, avoiding premature convergence and escaping from local optimum are also two inevitable topics for QPSO to achieve the global optimum. Several kinds of improvement for QPSO, such as parameters control, mutation operator with different probability distribution, selection operator, diversity control, hybridization, etc., have been investigated. A comprehensive review on QPSO by categorizing the publications on the improvements and applications can be found in [17]. However, among these methods