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Formalized model and analysis of mixed swarm based cooperative particle swarm optimization

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ABSTRACT

Natural phenomenon of mixed flocks indicates such principles as cooperation and social symbiosis among various species. Inspired by the organization and collective intelligence of natural mixed flocks, a mixed swarm based particle swarm optimization (MCPSO) is proposed to efficiently handle the trade-off between the global and local search in PSO. The approach divides all particles into two species, i.e., exploration species and exploitation species. Exploration species undertakes the coarse search in the solution space to discover new potential area, while the exploitation species is instructed accordingly to conduct fine search in its activity territory. Information sharing plays a crucial role between the two species, through the cooperative mechanism, not only does MCPSO avoid the optimum missed in a coarse search, but also it significantly saves void fine search. The proposed MCPSO is validated with well-known benchmarks confirming that the cooperative mixed swarm is an effective model for the swarm based searching, further proving that MCPSO is a robust global technique for complex optimization problems.

1. Introduction

Intelligent optimization techniques had been developed in the past decades with nature based inspirations, such as evolutionary computation, artificial neural network, artificial immune system, etc. Swarm intelligence is such an outcome inspired by the social behavior of certain natural biological systems, for example, bird flocking, fish schooling or ant colony etc. In general, the individual elements of those biological systems are low intelligent, small or weak in the nature, but a swarm of them become stronger and emerge high collective intelligence. Based on the swarm intelligence emerged in those natural systems, two notable optimization algorithms have been developed, particle swarm optimization (PSO) and ant colony optimization (ACO). Both of them have been applied to various complexes, nonlinear or dynamical problems, and have proved effective for optimizations.

As an intelligent optimization algorithm, PSO originally simulates the foraging behavior of bird flocks, and adopts the same population-based searching mechanism as evolutionary algorithms. In PSO, the individual standing for a candidate solution is described as a “particle”, which can fly through the solution space under the guide of its own and the other companion’s experiments, and approximates to the optimum gradually. Since the original version of PSO was proposed in 1995 by Kennedy and Eberhart [1], it has attracted massive attentions from various research backgrounds around the world. Owing to its nature of model simplicity and the profound sociality, PSO becomes very popular in many areas, including multi-modal complex problems [2,3], dynamic optimization [4], resource allocation [5] scheduling optimization [6,7] and many engineering applications. However, PSO suffers from the premature convergence problem as a stochastic algorithm, especially for the complex problems with large scale. In order to develop its optimization performance, a number of improved PSO variants have been presented in recent years, which mainly can be divided into the following categories.

The first category focuses on modifying the parameter sets of PSO. In order to limit the velocity of the particle, a parameter of inertia weight firstly was introduced into PSO in [8]. After that, several parameter modification based variants shortly were proposed, such as decreased linearly inertia weight [9], fuzzy technique based inertia weight [10]. Moreover, a method of time-varying acceleration coefficients was adopted to balance the local and the global search abilities in [11]. Besides the above modifications, a parameter called constriction coefficient was introduced to guarantee the PSO converging [3].

The second category can be seen to design different neighborhood topologies to prompt the information interaction among the particles. [12] developed alternative neighborhood topology constructions for particles, including the ring, the star, the wheel and the stochastic

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one. Another ring topology based on nicking [13] and two fully informed PSO versions [14,15] were developed respectively. Through the different information topologies, all the particles can get different informations to learn, validly improving the swarm diversity and alleviating the premature convergence of PSO. The similar ideas to improve PSO were proposed in Comprehensive Learning PSO (CLPSO) [16] and Social Learning PSO(SLPSO) [17]. Instead of learning from the global best of the swarm or a neighborhood and the personal best of its own in the standard PSO, each particle in CLPSO can randomly learn from the personal best of any other particles, while each particle in SLPSO can learn from the one of any better particles. In the meaning of information interaction, CLPSO and SLPSO can be regarded to adopt a whole random topology, which shows good performance for complex optimization problems.

Hybrid PSO variants are popular and can be regarded as the third category. Many intelligent computing algorithms have been combined with PSO, including ant colony optimization [6], artificial bee colony [18], cultural algorithm [19], memetic algorithm [20], etc. Furthermore, several techniques were introduced into PSO to develop hybrid PSO, such as mute strategy [21], chaotic theory [22], orthogonal learning [23], etc. Hybrid PSO variants prove valid but often is burdened with some computation costs.

The fourth category of PSO variants can be categorized to those controlling the swarm diversity adaptive with the process of a search. A feedback mechanism was adopted to modify the parameter sets that in turn improve the swarm diversity [24], the same mechanism was used to make the velocity mute toward the gradient direction guided by the swarm diversity [25]. Recently, [26] took advantage of the local stochastic to adjust the inertia weight to enhance the diversity. Moreover, multi-swarm also is a popular technique to maintain the swarm diversity, such as knowledge-based cooperative particle swarm optimization (KCPSO) [27], cooperative particle swarm optimization(CPSO) [28], Cooperatively coevolving particle swarm optimization(CCPSO) [29], and Dynamic Multi-Swarm Particle Swarm Optimizer [30]. Those versions can maintain the balance of the global search and the local search validly through the cooperative search of multi-swarm, and show good global performance to some degrees.

Besides the above-mentioned PSO variants, research attentions were also attracted to analyze the behavior and the convergent ability of PSO. Initially, the simplified particles are found to fly on an underlying continuous path of sine wave [31], and its behaviors mainly depend on the value of the control parameters [32]. In [3], the analysis of the stability properties of PSO was made, and a set of coefficients was proposed to control the convergent tendency of the algorithm. A similar analysis on a continuous-time version of PSO has been provided in [33]. More performance analysis can be found in [2] and [34], including the convergence, the Lyapunov stability, the controllable and the observable. All the researches show simple PSO not a global optimization, and many techniques should be introduced to guarantee it to be a global one.

It is evident that there are challenging problems ahead for PSO to develop from the perspective of a global optimization technique. In nature, it is a common phenomenon that birds of several species come together to be a mixed species flock. It is predicted that such flocking can make the best of different abilities of different species to defend predators or detect forages. Inspired and attracted by its existing mode and collective intelligence in nature, an initial simple idea of the cooperative PSO was proposed in [35]. We are inspired to develop a formalized model of mixed swarm based cooperative PSO, and make some comprehensive analysis about its search mechanism and optimization performance. The proposed model is to adopts exploration species and exploitation species, two cooperative ones, to construct a mixed swarm to carry on the search. Exploration species undertakes the coarse search in the solution space to discover new potential area, while exploitation species is assigned to take on the fine search following the survival territory of exploration species. When the coarse search and the fine search conducted in parallel, the two species keep the information sharing and learn from each other. Anyone switch of the behaviors in the mixed swarm are guided by a behavior control according to the global information shared on an information board. Through this cooperative search mechanism between two species, MCPSO can validly keep the balance of the global search and the local search.

The remaining of the paper is organized as the follows. Section 2 provides the formulations of standard PSO, while Section 3 analyzes the natural mixed species flocks and its inspiration, describes the architecture of the mixed swarm for optimization search. Section 4 provides the detailed search behavior and formalized description of MCPSO, and presents the analysis of its computational complex. Some experimental results and some comparison analysis about the proposed models are presented in Section 5. Finally, Section 6 concludes with some remarks.

2. Standard particle swarm optimization

Originally, PSO defines a swarm of particles to represent the potential solutions to an optimization problem. In order to search an optimum, each particle begins with an initial position randomly and flies through the D-dimensional solution space. The flying behavior of each particle can be described by its velocity and position. The update equations about the velocity and position are formulated as the follows:

$$v_{id}(t+1) = v_{id}(t) + c_1 r_1 (p_{id}(t) - x_{id}(t)) + c_2 r_2 (p_{gd}(t) - x_{id}(t)) \tag{1}$$

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1) \tag{2}$$

Here $X_i=(x_{i1}, x_{i2},\ldots, x_{id},\ldots, x_{iD})$ and $V_i=(v_{i1}, v_{i2},\ldots, v_{id},\ldots,v_{iD})$ represent the position vector and velocity vector of the ith individual respectively, while $_{Pi}=(_{pi1}, _{pi2},\ldots, _{pid},\ldots, _{piD})$ is the personal best position discovered by itself, $P_g=(p_{g1}, p_{g2},\ldots, p_{gd},\ldots, p_{gD})$ stands for the global best position caught by the whole swarm; c_1 and c_2 are two constants known as "cognitive" and "social" coefficients, which determine the weight of $_{Pi}$ and P_g on the velocity V_i; r_1 and r_2 are two random numbers generated by uniform distribution in the range [0, 1].

The equations above describe the original version of PSO by Kennedy and Eberhart [1]. Obviously, the update equation of velocity above consists of three components, including the inertia velocity component, a cognitive component and a social component. The cognitive component only takes into account the particle's own experiences, while the social component represents the information interaction among the particles. According to the research of Kennedy [36], the performance of the cognition-only model is inferior to the original one due to the absence of the social interaction among particles, while the social-only model is superior to the original PSO for some optimizations. Although the preliminary results from Kennedy seem to indicate that the social component may be more significant than the cognitive one, no determinate conclusions have been declared in the relative literatures.

The model is referred to as Gbest PSO when P_g is the best position for all particles, while the model is called as the Lbest PSO when P_g is only a neighborhood best for some particles. Due to using a single attractor to pulling all the particles towards it, the Gbest model offers a faster convergent rate but tends to converge prematurely. The Lbest model maintains multiple attractors in the swarm to improve the swarm diversity. Though the Lbest model can alleviate the premature convergence at some degrees, it is just at the cost of search speed and computation expenses. Here, we only consider the Gbest model in the following works.