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Heterogeneous comprehensive learning particle swarm optimization with enhanced exploration and exploitation

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ABSTRACT

This paper presents a comprehensive learning particle swarm optimization algorithm with enhanced exploration and exploitation, named as “heterogeneous comprehensive learning particle swarm optimization” (HCLPSO). In this algorithm, the swarm population is divided into two subpopulations. Each subpopulation is assigned to focus solely on either exploration or exploitation. Comprehensive learning (CL) strategy is used to generate the exemplars for both subpopulations. In the exploration-subpopulation, the exemplars are generated by using personal best experiences of the particles in the exploration-subpopulation itself. In the exploitation-subpopulation, the personal best experiences of the entire swarm population are used to generate the exemplars. As the exploration-subpopulation does not learn from any particles in the exploitation-subpopulation, the diversity in the exploration-subpopulation can be retained even if the exploitation-subpopulation converges prematurely. The heterogeneous comprehensive learning particle swarm optimization algorithm is tested on shifted and rotated benchmark problems and compared with other recent particle swarm optimization algorithms to demonstrate superior performance of the proposed algorithm over other particle swarm optimization variants.

1. Introduction

In order to solve multimodal, discontinuous, non-convex and non-differentiable optimization problems, researchers have developed population-based algorithms such as particle swarm optimization (PSO), genetic algorithm (GA), differential evolution (DE), evolutionary strategy (ES), evolutionary programming (EP) and so on. In population-based algorithms, finding the optimal solution of a problem is based on two cornerstones, namely exploration: global search, exploring all over the search space to find promising regions and exploitation: local search, exploiting the identified promising regions to fine tune the search for the optimal solution. Good convergence behavior of a population-based algorithm can be obtained when an appropriate balance between exploration and exploitation processes is found. Emphasizing on exploration will lead to waste of time searching over inferior regions of the search space and slow down the convergence rate. On the other hand, emphasizing on exploitation will cause loss of diversity early in the search process, thereby possibly getting stuck into a local optimum. Therefore, in the population-based evolutionary algorithms, it is important to obtain the balance between exploration and exploitation of the search space [1,2].

Among population-based algorithms, PSO is easy to implement and has performed well on many optimization problems. PSO is also known for having the ability to quickly converge to the optimal [5]. However, in PSO, all particles share its swarm's best experience (the global best) that can lead the particles to cluster around the global best. In case, if the global best is located near a local minimum, escaping from local optimum becomes difficult and PSO suffers diversity loss near the local minimum [5]. In order to balance the exploration behavior of global search and exploitation nature of local search in PSO, inertia weight w was firstly proposed by Shi and Eberhart [4]. Clerc and Kennedy also developed another control parameter called constriction coefficient χ to control the convergence tendency of the particle swarm, including exploration and exploitation abilities [6]. In [7], self-organizing hierarchical PSO (HPSO-TVAC) was introduced with time varying acceleration coefficients. With decreasing cognitive component and increasing social component, global exploration is enhanced to avoid premature convergence in the early stages and local exploitation is enhanced to converge to the global optimum solution during the latter stages of the search.

The neighborhood topologies also control PSO's exploration and exploitation abilities according to the information sharing among the particles in the swarm [8–10]. Based on the findings in

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[8,10], a fully-informed PSO (FIPS) was proposed in which information from fully connected neighborhood was used [11] and different neighborhood topologies were studied in [12]. In [13], best experiences from local neighborhood and global neighborhood were used in unified particle swarm optimization (UPSO) algorithm by combining their exploration and exploitation abilities. The paper mentioned that the neighborhood size should be selected properly to get trade-off between exploration and exploitation.

Instead of using neighborhood topology to learn the information from other particles, Liang proposed comprehensive learning particle swarm optimizer (CLPSO) in which each particle learnt from other particles' best experiences for different dimensions via a comprehensive learning strategy [14]. In CLPSO, learning probability curve is set so that the particles have different levels of exploration and exploitation abilities. In orthogonal learning particle swarm optimization (OLPSO), orthogonal learning strategy was developed in which a particle learnt from the combination of its own best experience (cognitive learning) and its neighborhood best experience (social learning) to compromise the balance between the exploration and exploitation search [15]. Efficient population utilization strategy for particle swarm optimization (EPUS-PSO) was presented in [16]. In EPUS-PSO, solution sharing and search range sharing strategies are proposed to share best information among the particles and to avoid the particles from getting trapped in a local optimum. Population size is varied by a population manager according to the status of the solution search [16].

The new learning strategy called scatter learning strategy was presented in a scattering learning particle swarm optimization algorithm (SLPSOA) [17]. In scatter learning strategy, the exemplar pool (EP) is constructed which is composed of a certain number of relatively high-quality solutions scattered in the solution search space and enables the particles to explore different regions. Then, the particles select their exemplars from EP using roulette wheel rule and the selected exemplar is used for a certain number of iterations to exploit the corresponding region thoroughly. A competitive swarm optimizer (CSO) was developed where neither personal best position nor global best position was involved in updating the particles' positions [18]. In CSO, the two particles are randomly selected to compete and the loser will update its position by learning from the winner and mean position of current swarm. The empirical analysis of exploration and exploitation abilities showed that CSO achieved a good balance between exploration and exploitation [18].

In [19], as a new approach to balance the exploration and exploitation in PSO, predator prey optimizer was developed, combining PSO idea with predator prey strategy. In predator prey optimizer (PPO), one predator particle is introduced to attract the best particle in the swarm while prey particles are repelled from the predator and the best. The balance between the two processes is influenced and controlled by the interactions of the predator and prey particles. In [20], attractive and repulsive PSO (ARPSO) was introduced with negative entropy into original PSO, encouraging high diversity and discouraging premature convergence in order to obtain trade-off between the two. Blackwell and Bentley also introduced the repulsive force to PSO and proposed the atomic swarm that is composed of equal number of charged and neutral particles so that there is a balance between exploration and exploitation [21].

In order to address the exploration and exploitation trade-off problem, heterogeneous particle swarm optimization was proposed in [22,23]. In heterogeneous PSO (HPSO) [23], the particles in heterogeneous swarms were allowed to follow different velocity and position updating rules from a behavior pool, thereby having the ability to explore and exploit throughout the problem search space. In [24], a multi-swarm PSO using charged particles (PSO-2S) was developed in which the search space was partitioned and two kinds of swarms were used, called main and auxiliary. In PSO-2S, the auxiliary swarms are initialized in different partitioned areas, using charged particles. After certain number of generations, main swarm is formed with the best individual of the auxiliary swarms to search for the optimum. In [25], a cooperative approach was applied to PSO (CPSO-S_k) in which the dimensionality of the search space was split and different swarms were used to search over different dimensions of a solution cooperatively. Multi-swarm idea have also been used for locating multiple optimal solution in [26] and for dynamic environments in [21,24,27].

From the PSO variants mentioned above, it is obvious that the main issue in PSO is to keep the balance between the exploration and exploitation and researchers addressed this issue by suggesting different methods. Inspired by those methods, a CLPSO with two subpopulation groups, called Heterogeneous CLPSO (HCLPSO), is proposed in this paper. Instead of relying on one method to balance the exploration and exploitation ability of PSO, this paper addresses the issue by the following methods: by using adaptive control parameters, by controlling the information sharing (or topology) among the particles, by using a learning strategy and by using heterogeneous swarm rather than homogeneous.

In this paper, a heterogeneous swarm is used where the swarm is divided into two subpopulations. Each subpopulation is assigned to carry out the exploration and exploitation search separately. Exploration and exploitation processes are enhanced without one process crippling the other. Comprehensive learning strategy is used to generate an exemplar for the particles to learn. In PSO, learning from the two exemplars, personal best and the whole swarm's best, can cause two problems. One is "oscillation phenomenon" [28] which can occur if the two experiences were in opposite directions. This makes the search ability inefficient and slows down the convergence speed of the algorithm. Another is "two steps forward, one step back phenomenon" [25] which causes the solution vector to be improved on some dimensions and to be declined on other dimensions as one exemplar may have good values on some dimensions and others may have good values on some other dimensions. Thus, in order to extract such useful information from different dimensions of different particles in the swarm, comprehensive learning (CL) strategy is used to generate a promising exemplar in the proposed algorithm.

Via comprehensive learning (CL) strategy, the exploration-subpopulation group learns for different dimensions from its own members' previous best experiences and its particles have high level of exploration ability. The exploitation-subpopulation benefits by learning from the best experiences of all particles in the swarm including the whole swarm's best experience and therefore, its particles have strong exploitation ability. Different learning probability values are specified for each particle in the swarm such that the particles from the exploration-subpopulation are not influenced by the exploitation-subpopulation. In this way, the information sharing among the particle is controlled and at the same time, the exploitation-subpopulation is able to exploit instantly new good regions discovered by the exploration-subpopulation. Besides, adaptive control parameters are used in the subpopulation groups to enhance exploration and exploitation. Therefore, this novel heterogeneous subpopulation structure is able to emphasize exploration and exploitation simultaneously without one process unfavorably influencing the other.

This paper is organized as follows: original PSO is introduced in Section 2 and the proposed HCLPSO is presented in Section 3. In Section 4, the performance of the proposed HCLPSO algorithm is evaluated using the benchmark problems and compared with other state-of-art PSO algorithms. The research limitation and future works are also discussed in Section 4. Finally, the paper is concluded in Section 5.