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A novel parallel multi-swarm algorithm based on comprehensive learning particle swarm optimization

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ABSTRACT

This article presented a parallel metaheuristic algorithm based on the Particle Swarm Optimization (PSO) to solve global optimization problems. In recent years, many metaheuristic algorithms have been developed. The PSO is one of them is very effective to solve these problems. But PSO has some shortcomings such as premature convergence and getting stuck in local minima. To overcome these shortcomings, many variants of PSO have been proposed. The comprehensive learning particle swarm optimizer (CLPSO) is one of them. We proposed a better variation of CLPSO, called the parallel comprehensive learning particle swarm optimizer (PCLPSO) which has multiple swarms based on the master-slave paradigm and works cooperatively and concurrently. The PCLPSO algorithm was compared with nine PSO variants in the experiments. It showed a great performance over the other PSO variants in solving benchmark functions including their large scale versions. Besides, it solved extremely fast the large scale problems.

1. Introduction

In recent years, many researchers have been working on optimization which is very important for many areas such as especially computer science, high performance computing, industrial engineering and mechanical engineering. Optimization problems are often NP-hard, complicated and time consuming (Torn and Zilinskas, 1989; Talbi, 2009). In this work, unconstrained global optimization problems (Schäffler, 2012), the subclass of global optimization, are tackled. Optimization methods are basically divided into four classes to solve these problems: exact methods, approximation algorithms, metaheuristic algorithms and greedy algorithms. Metaheuristic algorithms find the optimal solution or a solution close to the optimal solution within a reasonable amount of time although exact methods find the optimal solution. The exact methods are not very often used in practice because the solutions of multi-dimensional, multimodal real-world problems by them are very time consuming. On the other hand, heuristic methods are often used in practice because they find a good solution in a reasonable time.

Many metaheuristic algorithms were developed to solve the optimization problems and new algorithms have been also proposed. Swarm intelligence and evolutionary computation are two popular subclasses of the metaheuristic algorithms. Swarm intelligence contains particle swarm optimization (Kennedy and Eberhart, 1995), artificial ant colony algorithm (Dorigo and Stützle, 2004), artificial bee colony algorithm (Karaboga and Basturk, 2007), grey wolf optimizer (Mirjalili et al., 2014) etc. On the other hand, evolutionary computation contains genetic algorithm (Goldberg, 1989), memetic algorithm (Neri et al., 2011) and gene expression algorithm (Ferreira, 2006) etc.

As mentioned above, metaheuristic algorithms are very efficient to solve optimization problems. Particle swarm optimization (PSO) is one of them. PSO is developed by Kennedy and Eberhart (1995) is a population-based and metaheuristic optimization technique. It inspired from the social behaviors of bird and fish flocks. Each individual in the population, called particle, represents a potential solution. Particles scan the search area by following the current best solutions in the population and thus converge to the global optimum. Thanks to the success and the popularity of PSO, it has been used in many various areas such as logistics and transportation (Wu and Tan, 2009), bioinformatics (Correa et al., 2006), business (Yang et al., 2011), finance (Kendall and Su, 2005), data mining (Grosan et al., 2006), product design and manufacturing (Yıldız, 2009), automotive industry (Yildiz, 2012) and so on.

Rapid advances in science and technology trigger developments in the computation area as in all areas. As a result of these developments, problems to be solved by computers become larger

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and more complex and they cause the increments of the large-scale data. Thus, parallel computing and parallel algorithms are needed to solve these problems and to process the large-scale data.

In parallel computing, a task which is divided into subtasks is run synchronously on multiple processors to obtain quickly the results (Grama, 2003). Using parallel computing, the performance of an algorithm increases and large-scale problems are solved in a shorter time. Therefore, parallel computing has been used in many areas such as medical image processing (Zhu and Cochoff, 2010), bioinformatics (Zomaya, 2006), data mining (Zaki and Ho, 2000), finance (Hong et al., 2010) nowadays because data increases day by day. In this work, Jade software framework (Bellifemine et al., 2007) which is a middleware is used to develop the proposed parallel algorithm. The middleware is a software layer, which supports heterogeneous computers, networks and operating systems and allows developing parallel applications, between the operating systems and applications (Tanenbaum and Van Steen, 2007).

Metaheuristic optimization algorithms have usually a sequential structure. Although their usage reduces time complexity, the solutions of some real-world problems, such as in aerospace (Hasenjäger et al., 2005; Olhofer et al., 2001) and chemistry (Lucasius and Kateman, 1991), which occur in the academy and industry still take too long time. Thus, parallel computing is used together with metaheuristic algorithms both to decrease the search time and to increase the quality of the solutions (Alba, 2005). The objective of this work is to develop a new parallel metaheuristic algorithm in order to solve unconstrained global optimization problems, especially the large-scaled problems.

After literature review, it is seen that the CLPSO algorithm (Liang et al., 2006) has a better performance than the other PSO variants. As previously mentioned, even if the optimization techniques are used, the solutions of the some problems become difficult and take too long time. Therefore to face such difficulties, the improving of the CLPSO algorithm's performance is aimed by using parallel computing and we propose a new parallel multi-swarm CLPSO algorithm (PCLPSO) in this work. The performance of PCLPSO is demonstrated on the function optimization problems. The main contributions of this article are that the proposed algorithm (i) uses a new cooperation strategy, (ii) significantly speeds up the search, (iii) improves the quality of the obtained solutions, (iv) improves the robustness and (v) also solves large-scale problems.

This article is organized as follows: Section 2 presents a detailed review on the PSO variants and the parallel metaheuristic optimization approaches. The PSO algorithm, CLPSO algorithm and PCLPSO algorithm are presented in Section 3. Section 4 reveals the experimental results and analysis of PCLPSO in solving the unconstrained global optimization problems. Finally, the article is concluded in Section 5.

2. Related work

To obtain better solutions of the global optimization problems, some researchers have worked to improve the PSO algorithm and have proposed many PSO variants. Shi and Eberhart (1998) introduced a new parameter, called inertia weight. The inertia weight plays the role to balance between the global search ability and local search ability. The performance of PSO is better through the inertia weight because its chance is bigger in order to find the global optimum within a reasonable number of iterations. Clerc and Kennedy (2002) introduced a new parameter is called constriction coefficient. In the original PSO, the particles' velocities must be limited to control their trajectories. But, the PSO with the constriction coefficient both requires no explicit limit V_{max} and has a better performance. Kennedy and Mendes (2002) investigated the effects of various population topologies on PSO and proposed some methods to enhance the performance. They claimed that a population could move rapidly towards the best solution when the nodes in a topology were too close and communication passes too quickly. In Parsopoulos and Vrahatis (2005), UPSO was introduced that it aggregated the local and global variant of PSO using their exploration and exploitation abilities. Mendes, Kennedy, and Neves (2004), a new algorithm, called FIPS, was proposed. The main property of FIPS is that all neighbors can be a source to affect each other in FIPS although *gbest* and *pbest* are used in PSO. Namely, a particle uses information of all particles in the population. In Peram et al. (2003), a new dimension was added to the socio-cognitive learning process that is based on *pbest* and *gbest*. A particle also learns from its neighbor particles which have better performance. This approach changes only the velocity update equation. Thus, a wider search space is scanned and the probability of getting stuck in local optima is reduced. Van den Bergh and Engelbrecht (2004) proposed a cooperative approach (CPSO) where the large search space is separated into several smaller ones according to the number of the dimensions. Each smaller search space has own swarm that optimizes a one-dimensional problem. Thus, the swarm is divided into subswarms. These subswarms optimize cooperatively the different parts of a problem and the solution vector is composed of the results of the subswarms. In Tang et al. (2015), a multi-strategy adaptive particle swarm optimization (MAPSO) was proposed to search the global optimum in the entire search space with a very fast convergence speed. MAPSO changes dynamically the inertia weight according to the status of particles and introduces an elitist learning strategy to enhance the diversity of population. Liang et al. introduced a comprehensive learning PSO (CLPSO) in Liang et al. (2006). Instead of using a particle's *pbest* information in the original PSO, all other particles' *pbest* information is used to update the particle's velocity. Further, the *gbest* position in PSO is never used in CLPSO. With this strategy, CLPSO scans a larger search space and the probability of finding global optimum is increased. Therefore, CLPSO enhances significantly the performance of PSO. Unfortunately, the performance of many optimization algorithms becomes worse as the dimensionality of the search space increases. In de Oca, Aydın, and Stützle (2011), García-Nieto and Alba (2011), two modified PSO algorithms are introduced to solve large scale continuous optimization problems.

In the past few years, the number of research articles on the parallel metaheuristic optimization has increased. Fan and Chang (2009) proposed a PSO algorithm based on the parallel computing technique and Pareto dominance to solve multi-objective optimization problems. The master-slave architecture was implemented to communicate between sub-swarms. In Fan and Chang (2010), very large-scale multimodal functions were solved by using a parallel multiswarm PSO algorithm. To obtain a better performance, the search area was partitioned evenly and dynamically. Another parallel algorithm based on PSO was proposed by Kotinis (2011). Kotinis also employed the mutation and elitism strategies to improve the performance of PSO. In Li and Wada (2011), Li and Wada proposed a parallel PSO algorithm which reduced effectively the communication latency and improved the effectiveness of PSO on distributed environment. In Chaves-González et al. (2011), a parallel hyper-heuristic based on seven heuristics was proposed in order to solve complex optimization problems. To prove the performance of this algorithm, this approach was tested on a real-world problem in telecommunication. In recent years, many multi-objective evolutionary algorithms have been proposed and some of them have been used in the area of the robust engineering design optimization such as fluid mechanics and finite-element methods. The solution of