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Directionally Driven Self-Regulating Particle Swarm Optimization algorithm

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ABSTRACT

In this paper, an improved variant of the Self-Regulating Particle Swarm Optimization (SRPSO) algorithm is proposed that further enhances the performance of the basic SRPSO algorithm and is referred to as a Directionally Driven Self-Regulating Particle Swarm Optimization (DD-SRPSO) algorithm. In DD-SRPSO, we incorporate two new strategies, namely, a directional update strategy and a rotational invariant strategy. As in SRPSO, the best particle in DD-SRPSO uses the same self-regulated inertia weight update strategy. The poorly performing particles are grouped together to get directional updates from the group of elite particles. All the remaining particles are randomly selected to undergo either the SRPSO strategy of self-perception of the global search direction or the rotational invariant strategy to explore the rotation variance property of the search space. The performance of the DD-SRPSO algorithm is evaluated using the complex, shifted and rotated benchmark functions from CEC2013. These results are compared with seven current state-of-the-art PSO variants like Social Learning PSO (SLPSO), Comprehensive Learning PSO (CLPSO), SRPSO, etc. The results clearly indicate that the proposed learning strategies have significantly enhanced the performance of the basic SRPSO algorithm. The performance has also been compared with state-of-the-art evolutionary algorithms like Mean Variance Mapping Optimization (MVMO), Covariance Matrix Adaptation Evolution Strategy (CMA-ES) on the recently proposed numerically expensive optimzation CEC2015 benchmark functions whereby DD-SRPSO has provided competitive solutions. The results also indicate that the DD-SRPSO algorithm achieves a faster convergence and provides better solutions in a diverse set of problems with a 95% confidence level, thereby promising to be an effective optimization algorithm for real-world applications.

1. Introduction

Optimization has been an active research area for several decades for providing solutions to complex real-world problems. These problems have become extremely complex in the past few decades with the association of increasing dimensionality, differentiability, multi-modality and rotation characteristics in almost all the problems [1]. The demand for real-time numerical optimizer has also propelled the researchers to develop accurate, fast and computationally efficient optimization algorithms. Researchers have developed many numerical optimization techniques to achieve better solutions for these problems. Over the recent past, population based meta-heuristic optimization algorithms have gained much popularity in the research community as these algorithms have successfully provided better optimized solutions to many complex problems [2]. A general survey on the meta-heuristic optimization algorithms has been presented in [3,4]. In recent years, nature inspired optimization algorithms are being preferred over other population based metaheuristics due to their simplicity, efficiency and accuracy [3].

Among the nature inspired optimization algorithms, Particle Swarm Optimization (PSO) algorithm introduced in 1995 by Eberhart and Kennedy [5], has been a preferred choice of the research community because of its simplicity and lower computational requirements. PSO has shown promising performances on several complex real-world optimization problems [6–9]. The PSO algorithm is a population based search meta-heuristic. PSO is inspired from the social behavior of bird swarm and fish schooling in search of food. The behavior has been mathematically modeled for solving optimization problems. The members of the swarm are referred to as particles and they update their search patterns using both the exploration of the search space and the exploitation of

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the better solutions found by any of the particles. The process of exploration is performed using their own experience and the process of exploitation is performed using other members' experiences. The particles ensure their movement in the right directions by sharing their obtained best information in the entire searching process [10]. Similar to other population based algorithms, there is a likelihood that a group from the population can mislead other particles thereby resulting in premature convergence [11]. Existence of premature convergence in PSO has always attracted researchers to develop PSO variants that can overcome the above limitation [12–19].

PSO has gained a widespread appeal amongst researchers and different modifications, variations and refinements have been proposed for enhancing the performance of the basic PSO algorithm. In order to have a balance between exploration and exploitation capabilities of the PSO, an inertia weight ω was introduced [20] during the initial modifications in the algorithm. Later, the researchers tuned the inertia weight for better performance [21–24]. The growing popularity of PSO algorithm attracted researchers towards tuning other parameters [25–28] as well as investigating the neighborhood topology of the particles [29,30,11,31–33]. Two significant algorithms in the neighborhood topology are the Fully Informed Particle Swarm (FIPS) [34] and the Dynamic Multi-Swarm Particle Swarm Optimizer (DMSPSO) [35]. FIPS introduced a novel information flow process by using the weighted sum of all the neighboring particles for updating the position of a given particle and DMSPSO performed the position update using a dynamically changing neighborhood topology within the swarm. A complete survey of these modifications and refinements is available in [36]. Further, hybridization of PSO with other techniques to overcome its weaknesses have also been actively researched in recent years [37–40]. A comprehensive survey of hybridized PSO variants is given in [41,42].

The most active and a popular research area for improving the performance of the PSO algorithm has been the development of PSO variants using different learning strategies. These variants of PSO have provided promising improvements by significantly enhancing the convergence characteristics of the standard PSO algorithm. A novel algorithm with the concept of maximum fitness-to-distance ratio with respect to the particles using the personal best, global best and another particle's personal best was introduced in [43] to update the velocity of any particle. The Comprehensive Learning Particle Swarm Optimizer (CLPSO) [14] introduced a novel concept of particles learning through the information of all other particles' personal best solutions. Several other variants were introduced with unique learning strategies such as teaching and peer learning PSO [44], distance based locally informed PSO [45], multi-layer swarms [46], multi-swarm strategy [47] and cooperative swarm strategy [48]. The increasing complexity in the nature of real-world problem has raised several new difficulties; among them the major one being the rotation of search space demanding a rotationally invariant optimization algorithm for providing accurate solutions. The dimensions of the problem become non-separable when the problems are rotated. Hence, it is extremely difficult for any rotationally variant optimization algorithm to locate the true optimum solution. Therefore, any algorithm that optimizes the objective functions separately along each dimension cannot locate the true optimum solution. It has been theoretically proven in [49] that the PSO algorithm is rotationally variant since the velocity update is carried out along dimension by dimension. Therefore, a rotationally invariant PSO algorithm referred to as Standard Particle Swarm Optimization 2011 (SPSO-2011) [50] was developed which has the rotational invariance property to address this issue. The rotational invariance characteristic has provided a faster convergence towards the region of global optimum in rotated functions. All these PSO variants have successfully improved the convergence characteristics of the basic PSO algorithm, but the performance has always been a concern due to the existence of premature convergence. This limitation motivated the researchers to adapt learning strategies inspired from human learning principles and develop intelligent PSO variants with human-like learning characteristics for better convergence.

Human beings are known to be intelligent and possess excellent social interaction for the development of highly efficient problem solving skills [51]. Therefore, any optimization algorithm should prove to be more effective by utilizing human learning principles in the search for the optimum as indicated in [52]. Several optimization algorithms possessing human-like characteristics have been recently proposed [53,54]. Further, human self and social cognition have been applied to the PSO algorithm for achieving maximum benefit [55,56]. In [57], the idea of intelligent utilization of human resources for better productivity has been applied to the PSO algorithm. The social learning scheme has been adopted from human learning principles and applied to the particles in Social Learning Particle Swarm Optimization (SLPSO) algorithm [58] to allow the particles learn from any better performing particle instead of just from the best particle. Such a collaborative strategy has significantly enhanced the performance of PSO algorithm. Recently, in Self-Regulating Particle Swarm Optimization (SRPSO) algorithm [59], human self-regulation and self-perception strategies have been applied to the PSO algorithm for better exploration and exploitation of the search space. The learning scheme used by SRPSO has significantly enhanced the performance and faster convergence towards the global optimum region has been observed in most of the functions.

In human learning psychology, it has been shown that learning in human beings is not limited to self-cognizance since humans perform learning using multiple information processing strategies [51]. Collaborative and cooperative socially shared information help in attaining the maximum gain from the environment. SRPSO algorithm has utilized only the self-regulation for the best particle and self-perception for all the other particles. Socially shared information will help the particles to acquire a better learning scheme that can lead them towards potentially better solutions. This has been proven in the recently proposed improved SRPSO algorithm [60] where a fixed number of top four particles have been used to guide the last two poorly performing particles. Inspired from these findings, we introduce here a new directional update strategy for the poorly performing particles to extract better contributions from these poorly performing particles towards convergence. Performance of SRPSO on rotated problems is not that effective as shown in earlier studies [59]. To overcome this problem, a rotational invariant strategy is also implemented in the basic SRPSO algorithm for tackling the rotated functions. In this paper, we are introducing both a directionally updated and a rotationally invariant SRPSO algorithm referred to as a Directionally Driven Self-Regulating Particle Swarm Optimization (DD-SRPSO) algorithm. In DD-SRPSO, the best particle will continue to use the self-regulated inertia weight strategy of SRSPO. All the poorly performing particles update their search patterns having a full perception of the global search directions. Further, they get the directional updates from the group of elite particles. The rest of the particles are randomly selected to either perform a search using self-perception on the global search direction strategy of SRPSO or use the rotational invariant strategy to explore the rotation variance property of the search space. These new learning strategies will provide the particles rotational invariance characteristics as well as enhance the awareness of the search space for the poorly performing particles. The effects of the proposed learning schemes in DD-SRPSO on the convergence of the SRPSO algorithm have