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Dynamic social behavior algorithm for real-parameter optimization problems and optimization of hyper beamforming of linear antenna arrays

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ABSTRACT

The ever evolving complexity of real-world problems had become an impetus for the development of many new and efficient optimization algorithms. Meta-heuristics based on evolutionary computation and swarm intelligence are successful examples of nature-inspired optimization techniques. In this work, a new Dynamic Social Behavior (DSB) algorithm is proposed to solve global optimization problems. The DSB algorithm is based on the simulation of cooperative behavior of animal groups. In the proposed algorithm, individuals emulate the interaction of individuals based on biological laws of cooperative colony. This algorithm partially adopts the foraging strategy of animal groups and utilizes recruitment signal as a means of information transfer among individuals. In order to illustrate the proficiency and robustness of the proposed algorithm, it is compared with other well-known evolutionary algorithms. The comparison examines several series of widely used benchmark functions and an engineering problem on hyper beamforming optimization. The results testifies the superior performance of DSB compared with other state-of-the-art meta-heuristics.

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1. Introduction

Meta-heuristics optimization algorithms has attracted great interest in the last two decades. Application of meta-heuristic algorithms have permeated into almost all areas of sciences, engineering and industries, from computational intelligence to business planning, from data mining to optimization, and from bioinformatics to industrial applications.

Despite the popularity and success of meta-heuristics, there remains a big question of which meta-heuristic technique is best suited to solve all optimization problem. In this connection, the No Free Lunch (NFL) theorem (Wolpert and Macready, 1997) would be very much relevant to answer the question. According to this theorem, it is impossible to have a meta-heuristic that is best suited for all optimization problems. Simply put, a specific meta-heuristic could perform extremely well on a set of problem and may show a poor performance on another set of problems. In this regard, the findings of NFL gives motivation to develop new meta-heuristics which makes this field of study highly active over the years.

Meta-heuristics algorithms are generally based on mathematical programming or formal logic which makes it an effective solver for complex optimization problems compared to conventional Evolutionary Algorithm (EA) and Swarm Intelligence (SI) methods. In order to improve the solution quality in EA, the population have to determine whether to explore the unexplored search space or to exploit the previously evaluated positions. The ability of an EA to search for the global optimum very much depends on its ability to find the proper balance between the exploration of the search space and exploitation of existing elements. Pure exploration increases the potential to seek for new solutions but degrades the precision of the evolutionary process. Likewise, pure exploitation enhances existing solutions but adversely causes the evolutionary process to get stuck in local optima. Up to date, the issue of achieving an ideal exploration–exploitation balance is still an open ended subject matter within the framework of evolutionary algorithms.

Generally, EA exhibits the uniform behavioral pattern as the individuals are defined with the same characteristics. Therefore, the algorithm lacks the search operator to generate a scenario with different individual characteristics. By incorporating these type of operators, the algorithm characteristics such as population diversity or searching capabilities could be improved. In branch of SI, quite a number of algorithms have emerged in the past decades. However, several algorithms such as PSO, ABC and the more recently proposed GWO are widely employed and studied among researchers. Nevertheless, these algorithms exhibit

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several shortcomings such as low solving precision, inability to escape from local minima and premature convergence (Yu and Li, 2015). These deficiencies are caused by the search operators which are employed to manipulate the individual positions. In the case of PSO, the position of every individual is updated in the subsequent iteration cycle based upon the inclination to move towards the best individual in the entire population. In the case of ABC, a randomly chosen individual will be the center of attraction whereas in the case of GWO, the attraction is directed towards the position of the best three agents. Even though such operators encourages dynamic behavioral pattern, the operator tends to divert the entire population towards the best particles or causes the population to diverge without control as the algorithm evolves. This in turn damages the exploration–exploitation balance and leads to premature convergence.

In this paper, a new SI based algorithm inspired by social behavior of communal groups named Dynamic Social Behavior (DSB) is proposed. This work attempts to find the proper mechanism to balance the exploitation and exploration with the ability to track the best solution. The employment of community based social behavior as a metaphor introduces new concepts in the field of evolutionary computing. The concepts involve dividing the population into various search categories and apply collective knowledge search operators to each categories. This strategy allows the population to maintain its size and yet makes it possible to enhance the exploration–exploitation balance. The social behavior element in DSB introduces a new computational mechanism which has three distinctive descriptions. Firstly, every individual is evaluated separately according to their behavioral characteristics. Secondly, all the members of the population share the same communication mechanism to allow the dissemination of crucial information pertaining to the process of changing the search operators. Thirdly, the search operators utilize the global information (positions of all the individual types) to modify the position of a particular individual type.

The proposed algorithm has been tested by solving the CEC 2005 benchmark problems as well as a complex real world problem related to hyper beam antenna design. The optimization of hyper beamforming is considered as a complex problem as it has strong nonlinearities with many local minima. An efficient optimization algorithm is required to generate the optimal hyper beam radiation pattern. The DSB algorithm is benchmarked with the original PSO, ABC and GWO algorithms respectively. This approach of benchmarking with the original algorithms was suggested in Fong et al. (2016) to prove the novelty of any new meta-heuristic design (the inner designs are fundamentally different from existing algorithms) as the variants of the original algorithms have several similar and widely used core components from the original algorithm. The results display a high performance of DSB in searching for a global optimum and as well as in generating optimal hyper beams.

This paper is organized as follows. Section 2 presents a literature review on SI algorithms. Section 3 describes the proposed DSB algorithm in detail. The problem descriptions and evaluation methods are outlined in Section 4 whereas Section 5 presents the experimental results followed by discussion. Finally, Section 6 concludes the work and suggests directions for future studies.

2. Literature review

Meta-heuristic algorithms are often nature-inspired and can be divided into three main branches namely evolutionary (EA), physics-based and SI algorithms. The first branch, EAs are generally inspired by concepts of natural evolution. Generally, the optimization is done by generating an initial random population and evolving the population over a period of certain iteration values. During each iteration, a new set of population would be created by imposing certain sets of operators on the previous generation. These sets of operators will ensure that the best candidate will have higher probability to participate in the generation of the new population thus creating a better population compared to the previous generation(s). This is the general principles of how an initial random population is evolved over the course of generations. Some of the most prominent EAs are Genetic Algorithm (GA) (Goldberg, 1989), Genetic Programming (GP) (Koza, 1992), Evolutionary Programming (EP) (Yao et al., 1999), Evolution Strategy (ES) (Beyer and Schwefel, 2002), Differential Evolution (DE) (Storn and Price, 1997) and Biogeography-Based Optimizer (BBO) (Simon, 2008).

The second branch of meta-heuristics focuses on physics-based techniques that mimics certain physical laws. Physical rules such as electromagnetic force, gravitational force, weights and inertia force are applied to propel the movement of individuals in the search space. This mechanism is what differentiates EAs and physics-based techniques. Some of the most popular algorithms are Gravitational Search Algorithm (GSA) (Rashedi et al., 2009), Curved Space Optimization (CSO) (Moghaddam et al., 2012), Gravitational Local Search (GLSA) (Hosseinabadi et al., 2015), Charged System Search (CSS) (Kaveh and Talatahari, 2011), Central Force Optimization (CFO) (Formato, 2009), Small-World Optimization (SWO) (Xiaohu et al., 2009) and Artificial Chemical Reaction Optimization (ACROA) (Alatas, 2011).

The third branch of meta-heuristics is the SI algorithms which will the prime focus of this work. The mechanism of SI algorithms are almost similar to physics-based algorithm but the search process is purely inspired by the social behavior of swarms, flocks, herds or schools of creatures in nature. The individual navigation is done by imposing certain operators based on the mathematical model of social behavior of communal groups and collective social knowledge. Some of the SI algorithms are as follows:

- Ant Colony Optimization (ACO) (Dorigo and Stützle, 2004).
- Cuckoo Search (CS) (Yang, 2013).
- Firefly Algorithm (FA) (Yang, 2013).
- Bat Algorithm (BA) (Yang and He, 2013).
- Dolphin Partner Optimization (DPO) (Shiqin et al., 2009).
- Monkey Search (MS) (Mucherino and Seref, 2007).

Some of the popular SI algorithms are Particle Swarm Optimization (PSO) (Kennedy and Eberhart, 1995), Artificial Bee Colony (ABC) (Karaboga and Basturk, 2007) and the recent Grey Wolf Optimizer (GWO) (Mirjalili et al., 2014). PSO is represented by a swarm particles and their respective positions in the search space denotes the possible solution for the optimization problem. PSO utilizes the information of individual experience and socio-cognitive tendency to manipulate the movements of these particles. These two kinds of information correspond to cognitive learning and social learning which will eventually lead the population to perform better optimization (Yu and Li, 2015). ABC mimics the collective behavior of bees in finding food sources. The bees are divided into three groups namely the scout bees, the onlooker bees and the employee bees. The scout bees are responsible for exploring the search space, whereas the onlooker and the employee bees exploit the potential solutions found by scout bees (Mirjalili et al., 2014). The GWO is a recently proposed SI algorithm which mimics the social leadership and hunting behavior of grey wolves in their natural habitat. The population is divided into four groups: alpha, beta, delta and omega. The first three groups of wolves will guide the other wolves towards the promising areas of the search space.

Even though PSO, ABC and GWO are one of the most popular swarm algorithms for solving complex optimization problems, they display certain flaws such as premature convergence, inability to jump over local optima and prone to stagnation in local solutions (Wang et al., 2011; li Xiang and qing An, 2013; Mirjalili et al., 2014). Such problems could have been caused by the set of operators applied on each individual positions. In the case of PSO, every individual position is updated during every iteration based on the attraction towards the position of the best individual seen so far. In ABC, the individual position update is done based on attraction towards randomly chosen individuals whereas in GWO, the attraction is towards a fixed set of individuals. As the iteration evolves, these operators cause the entire population to revolve around the best individual or diverges without control. In

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