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Ageist Spider Monkey Optimization algorithm

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ABSTRACT

Swarm Intelligence (SI) is quite popular in the field of numerical optimization and has enormous scope for research. A number of algorithms based on decentralized and self-organized swarm behavior of natural as well as artificial systems have been proposed and developed in last few years. Spider Monkey Optimization (SMO) algorithm, inspired by the intelligent behavior of spider monkeys, is one such recently proposed algorithm. The algorithm along with some of its variants has proved to be very successful and efficient.

A spider monkey group consists of members from every age group. The agility and swiftness of the spider monkeys differ on the basis of their age groups. This paper proposes a new variant of SMO algorithm termed as Ageist Spider Monkey Optimization (ASMO) algorithm which seems more practical in biological terms and works on the basis of age difference present in spider monkey population. Experiments on different benchmark functions with different parameters and settings have been carried out and the variant with the best suited settings is proposed. This variant of SMO has enhanced the performance of its original version. Also, ASMO has performed better in comparison to some of the recent advanced algorithms.

1. Introduction

A metaheuristic refers to a high level problem independent framework which helps to develop heuristic optimization algorithms [1]. Any approach to problem solving, learning or discovery which focuses on immediate near optimality rather than exact results, using practical methods can be termed as a heuristic. Metaheuristics are developed scientifically to find a solution that is “good enough” in a computing time that is “small enough” [2–4]. The present trend to use heuristic techniques over exact ones is due to fact that many real world problems have been shown to remain forever intractable to exact algorithms, regardless of the ever increasing computational power, simply due to unrealistically large running times [5]. History and various trends related to metaheuristics are mentioned in [5]. One such approach is SI which is a result of collective behavior of different agents present in the population.

SI is a discipline which deals with artificial and natural systems, these systems are composed of swarms of homogeneous individuals and instead of everyone depending on a single central unit, all units are self-organized and they cooperate and share information to carry out their necessary tasks. The collective behavior of the individuals resulted from local interactions with each other and their environment is known as swarm intelligence. It is a metaheuristic approach which makes use of nature inspired techniques to solve optimization problems, the term was introduced by Gerardo Beni in 1989 [6], in the context of cellular robotic systems. A number of natural systems are studied under SI like schools of fish, ant colonies, bird flocks, bee colonies, herds of animals, etc. The engineering application of swarm intelligence is to exploit the understanding of the systems and design systems to solve problems of practical relevance.

The recent advancements in SI have shown its tremendous capability in solving complex problems which otherwise is impossible to solve with other naive approaches and therefore has great application in artificial intelligence. A lot of research has been done and is still

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going on to further improve the potential of SI in solving real time optimization problems. A number of nature inspired algorithms like ant colony optimization (ACO) [7] and particle swarm optimization (PSO) [8], artificial bee colony optimization (ABC) [9], bacterial foraging optimization (BFO) [10] has been proposed. These belong to the classes that are based on population, intelligent foraging behavior, social foraging behavior and many more. Early studies [10] of swarm behavior employed mathematical models to simulate and understand the swarm behavior. Three basic rules composing simplest mathematical model are:

- Move in the same direction as your neighbors.
- Remain close to your neighbors.
- Avoid collisions with your neighbors.

Craig Reynolds created programs called *boids* [1] in 1986, these programs simulate the swarm behavior following the above rules. Many current simulation models implement swarm behavior by means of concentric *zones* around each individual like zones of repulsion, alignment and attraction. Researchers, in order to find out as to why animals show swarm behavior, have been developing and studying evolutionary models simulating the population of evolving algorithms. Researchers have developed many algorithms and their improvements in recent years. Among them are various improvements of previously proposed evolutionary and swarm intelligence inspired algorithms.

Yu et al. [11] proposed enhanced comprehensive learning particle swarm optimization (ECLPSO) which improved the performance of CLPSO [12] by introducing perturbation rate and adaptive particle probability to the original algorithm. SP-PSO and SG-PSO [13] consider the effect of second best personal and global position for updating positions of other particles, respectively. Superior solution guided particle swarm optimization (SSG-PSO) [14] maintains and updates a collection of superior positions for updating positions of particles in the swarm. Scatter learning particle swarm optimization (SLPSO) [15] creates a pool of high quality solution scattered throughout search space called exemplar pool that makes particles to select their exemplars from the pool using the roulette wheel rule.

Recent research tries to improve performance of PSO by incorporating various elements of human learning principles within them. Social learning PSO (SL-PSO) [16] introduces a social learning mechanism into PSO such that particle position is updated based on historical information. To empower the searching particles with human like characteristics dynamic mentoring and self-regulation based PSO (DMeSR-PSO) [17] algorithm incorporates a dynamic mentoring scheme along with a self-regulation scheme in the classical PSO algorithm. Competitive and cooperative PSO with ISM (CCPSO-ISM) [18] proposes an information sharing mechanism (ISM) to improve the performance of PSO. Self-regulating particle swarm optimization (SRPSO) [19] algorithm incorporates best human learning strategies within PSO for finding the optimum solution. Adaptive division of labor (ADOL) PSO (ADOLPSO) [20] adopts two new operators, convex operator and reflectance operator to generate new particles from the memory swarm.

Differential Evolutionary (DE) [21] algorithm is an evolutionary search heuristic proposed by Storn and Price in 1995. To improve its performance, Jana et al. proposed Levy distributed DE (LdDE) [22] which control each of its parameters by levy distribution. DE with auto-enhanced population diversity (AEPD-JADE) [23] is proposed to identify the moments when a population becomes converging or stagnating by measuring the distribution of the population in each dimension. Harmony search algorithm [24] is a metaheuristic optimization method developed by Geem et al. imitating the music improvisation process where musicians improvise pitch of their instruments by searching for a perfect state of harmony. Valian et al. proposed IGHS [25] algorithm which presents an improved harmony search algorithm using the swarm intelligence technique.

Gao et al. proposed artificial bee colony algorithm based on information learning (ILABC) [26] which divides the whole population into sub-populations and dynamically adjusts size of sub-population. In enhanced artificial bee colony (EABC) [27] algorithm, two new search equations are presented to generate candidate solutions in the employed bee phase and the onlookers phase, respectively.

Inspired by the behavior of spider monkeys, Bansal et al. proposed an algorithm based on fission–fusion social structure. This algorithm is known as spider monkey optimization (SMO) [28] mimics the social behavior of a south American species of monkeys called spider monkeys, those belong to the class of nature inspired algorithms (NIA) [6]. The necessary principles of intelligent behavior are implemented in the social behavior of monkeys that are *self-organizing* in foraging behavior of monkeys while searching for food or mating and *division of labor* to divide the main group into subgroups for independent foraging. The fitness of the monkey at some particular position refers to its nearness to the global optimum value required, decides the superiority of food and affects behavior of other spider monkeys. The two main parts of an optimization problem, i.e. exploration and exploitation, need to be balanced. While searching for optimum solution the algorithm maintains the balance between deviation and selection processes which ensure exploration and exploitation, respectively.

Recently published modified variants of SMO have shown improvement in its performance, i.e. modified position update in spider monkey optimization (MPU-SMO) [29] that makes use of golden section search (GSS) to enhance performance of SMO. Kumar et al. proposed self-adaptive SMO (Sa-SMO) [30] with algorithm parameters being self-adaptive in nature and tournament selection based spider monkey optimization (TS-SMO) [31] proposed by Gupta et al. replaces the fitness proportionate probability scheme of SMO with tournament selection based probability scheme with an objective.

This paper proposes a new variant of SMO called as Ageist SMO (ASMO) which works on the basis of the fact that not all monkeys in the population are alike; they belong to different age groups and have different levels of activity. Some monkeys are more expeditious than others and, therefore, behave differently from others.

The rest of the paper is organized as follows: introduction is followed by Section 2 that contain details of SMO algorithm, proposed approach of the algorithm is explained in Section 3. A detailed analysis on different benchmark functions for clear understanding and comparison is given in Section 4. Section 5 concludes the paper on the basis of results obtained.