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Magnetic-inspired optimization algorithms: Operators and structures

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A B S T R A C T

A novel optimization algorithm, called the Magnetic Optimization Algorithms (MOAs), is proposed in this paper which is inspired by the principles of magnetic field theory. In MOA, the possible solutions are some magnetic particles scattered in the search space. In this respect, each magnetic particle has a measure of mass and magnetic field according to its fitness. In this scheme, the fitter magnetic particles are more massive, with stronger magnetic field. In terms of interaction, these particles are located in a structured population and apply a long range force of attraction to their neighbors. Ten different structures are proposed for the algorithm and the structure that offers the best performance is found. Also, to improve the exploration ability of the algorithm, several operators are proposed: a repulsive short-range force, an explosion operator, a combination of short-range force and explosion operator and a crossover interaction between the neighboring particles. In order to test the proposed algorithm and the proposed operators, the algorithm is compared with a variety of existing algorithms on 21 numerical benchmark functions. The experimental results suggest that the proposed algorithm outperforms some of the existing algorithms.

1. Introduction

Inspired by nature, many researchers have proposed new sets of algorithms and tools, particularly in the realm of artificially intelligent systems. Optimization is one such general aspect of intelligence, for which different imitations of nature are developed. Some of the first major efforts in this regard were the Evolutionary Programming (EP) [1] and Evolutionary Strategy (ES) [2]. The improved version of these two algorithms, called the Fast Evolutionary Programming (FEP) [3] and Fast Evolutionary Strategy (FES) [4] were then proposed. Simulated Annealing is another group of algorithms that is inspired from annealing in metallurgy [5]. The other group of algorithms is the Genetic Algorithms which are arguably the most famous population based algorithms and are inspired by the Darwinian natural evolution of species. A more recent set of population based algorithms is the Swarm Intelligence which was inspired by the collective behavior of flocks. Among these are the Synthetic Predatory Search Strategy which is inspired by the behavior of predators and preys [6], Ant Colony Optimization inspired by the behavior of ants [7], Particle Swarm Optimization inspired by the bird flocks [8], Bacterial Chemotaxis algorithms inspired by the bacterial chemotaxis model [9], Bacterial Foraging Optimization [10], Quantum Evolutionary Algorithms [11], Society and Civilization Optimization based on the simulation of social behavior [12], Group Search Optimizer [13] and Chemical Reaction Optimization [14]. These population based optimization algorithms promise more robust search due to their parallel nature. The main challenge in such algorithms is how to combine existing knowledge and create a synergism in the population of solutions to better accelerate their convergence to globally optimal solutions.

Evolutionary algorithms aim to provide better diversity by probabilistic recombination of solutions. One way to preserve diversity in the population is by structured EAs such as distributed [15] and cellular algorithms [16,17]. In distributed evolutionary algorithms, the population is partitioned into a set of islands where an isolated EA is executed on each island. In Cellular EAs (CEAs), the individuals are located in a grid structured population and each individual interacts with its neighbors. These types of decentralized algorithms provide a better sampling of the search space and thus improve the performance of EAs [16]. Rudolph and Sprave were the first to propose the cellular structure for genetic algorithms.

In the Particle Swarm Optimization algorithm, the fitness of the particles in the population is found and each particle tries to imitate the best particle(s) in the population. Each particle finds the best particle globally and adjusts its velocity towards the location of the best particle. There are several works that have tried to improve the performance of this basic PSO strategy.

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In [18], for example, a cooperative particle swarm optimizer is proposed, where multiple swarms cooperatively optimize different components of solutions. A comprehensive learning particle swarm optimizer is proposed in [19], which uses a novel learning strategy based on the historical best information of all particles to update the velocity of the particles. For learning to play games, Ref. [20] uses PSO to train neural networks and to predict the desirability of states in the leaf nodes of a game tree. To solve multi-modal optimization problems and to track multiple optima in dynamic environments, Ref. [21] proposed a species-based particle swarm optimizer. In another similar work, Ref. [22] uses multi-swarms PSO that is specially designed to work in dynamic environments. Ref. [23] proposes a novel parameter automation strategy for the particle swarm algorithm. They propose time-varying acceleration coefficients and inertia weight factor to control the convergence of the algorithm.

Despite being efficient and thus widely used in a variety of applications, the conventional PSO has some weaknesses. One, for example, is that it is only the best particle(s) that affect the motion of other particles, and the inferior particles do not influence the search process. The algorithm hence ignores important information that lies within the particles with low fitness. In this sense, a paradigm that gives a chance to the inferior particles to affect other particles can improve the performance. This encouraged us to propose a new scheme for interaction among the particles. The MOA, recently proposed by authors in [24], is a new paradigm of interaction for optimization that is based on the principles of attraction/repulsion among magnetic particles. Unlike other natural fields such as gravitational that always attracts and electrical that always either attracts or repulses based on sign difference/similarity, magnetic particles exhibit both attraction and repulsion to a given particle based on their relative polarity. As will be shown in this research, this dual function can be useful in optimization to balance exploitation versus exploration. In this algorithm, the particles are attracted/repulsed to/by their neighboring particles in a lattice-like structured population. In [24], a basic version of this paradigm of interaction that accounted only for long range force of attraction, without the repulsion, was successfully applied to 14 numeric benchmark problems. Since proposed, the algorithm has been used on some applications including training a multi-layer perceptron training [25] and a traveling salesman problem [26]. A binary version of the algorithm is also proposed in [27]. In this paper, we extend our earlier algorithm by investigating the effect of short-range repulsion in addition to several other new operators. The short range force is activated only when the distance between two particles is less than a certain threshold. The repulsive short-range force aims to maintain diversity of population and thereby to improve the exploration ability of the proposed algorithm. This characteristic makes the algorithm capable of effectively searching the optimization landscape as will be shown in this paper. Several other operators including an explosion operator, a combination of short-range repulsion and explosion operators, as well as a crossover interaction between the particles are also investigated. The proposed algorithm is compared with a group of existing algorithms including GA [28], PSO [8], Evolutionary Programming (EP) [1], Fast Evolutionary Programming (FEP) [3], Evolutionary Strategy (ES) [29], Fast Evolutionary Strategy (FES) [30], Ma-ssw-chains (MASSW) [31] and Differential Evolution (DE). Experimental results on 21 benchmark functions show that the proposed algorithm consistently outperforms its basic competing alternative PSO paradigm and, on most of the problems, performs better than the existing algorithms. These benchmark algorithms are chosen to provide adequate comparison with the existing algorithms.

This paper is organized as follows. The basic Magnetic Optimization Algorithm is introduced in Section 2. Section 3 proposes four novel operators: the short-range repulsion (SRR), explosion (EXP), hybrid explosion-repulsion (HER) and crossover interaction MOA (X-MOA) to improve the performance of MOA. For proper comparison, in Section 4, the best parameters for the proposed MOA and its operators, as well as parameters of rival algorithms for each of the 21 numerical benchmark functions are separately determined. In Section 5 several structures are proposed and the effect of structure on the performance of the population is examined. Section 6 tests the proposed algorithm on 21 numerical functions and compares it with different algorithms. Finally, Section 7 concludes the paper.

2. Magnetic Optimization Algorithms

Electromagnetic force is one of the four fundamental forces in the universe. This force has a long-range effect, meaning its effect disappears only when the distance between the two particles is infinite. Unlike other fundamental forces, in magnetic field theory, there exist two types of attractive and repulsive forces. In gravity theory for example, there is only attractive force. In electrical field, if two particles have different charges, they perpetually attract each other, and having a similar charge indicates that they repulse each other. In the magnetic field theory on the other hand, two particles can repulse or attract each other relative to their polarity. Inspired by this paradigm, this paper proposes a novel Magnetic Optimization Algorithm, in which the possible solutions are some magnetic particles that can apply attractive long-range force and repulsive short range force on one another. To investigate the effect of various operators, the basic MOA algorithm only accounts for the attractive long-range force. Extensions on the basic MOA with four other types of operators such as SRR, EXP, HER, and X-MOA are investigated in the algorithm's second stage of development. Furthermore, in MOA, the magnetic particles operate in a lattice like interactive population as shown in Fig. 1.

The pseudo-code of the proposed optimization algorithm is briefly shown below and is described in the following steps:

Procedure Basic MOA
begin
  $t=0$
1. initialize X^0 with a structured population
2. while not termination condition do
  begin
    $t=t+1$
3. evaluate the particles in X^t and store their performance in magnetic fields B^t
4. normalize B^t according to Eq. (2)
5. evaluate the mass M^t for all particles according to (3)

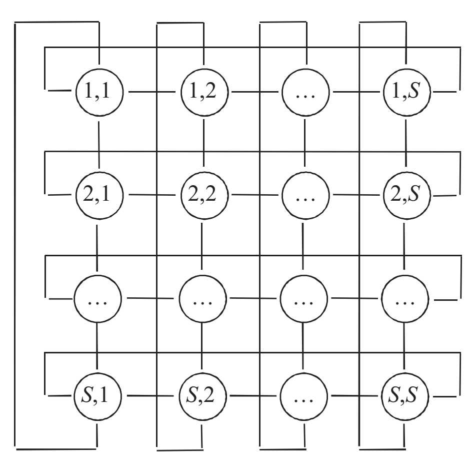

Fig. 1. The proposed cellular structure for the population with the size of S.