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Stochastic Fractal Search: A powerful metaheuristic algorithm

Hamid Salimi

School of Mathematics and Computer Science, University of Tehran, Tehran, Iran

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ABSTRACT

Evolutionary Algorithms (EAs) are well-known terms in many science fields. EAs usually interfere with science problems when common mathematical methods are unable to provide a good solution or finding the exact solution requires an unreasonable amount of time. Nowadays, many EA methods have been proposed and developed. Most of them imitate natural behavior, such as swarm animal movement. In this paper, inspired by the natural phenomenon of growth, a new metaheuristic algorithm is presented that uses a mathematic concept called the fractal. Using the diffusion property which is seen regularly in random fractals, the particles in the new algorithm explore the search space more efficiently. To verify the performance of our approach, both the constrained and unconstrained standard benchmark functions are employed. Some classic functions including unimodal and multimodal functions, as well as some modern hard functions, are employed as unconstrained benchmark functions; On the other hand, some well-known engineering design optimization problems commonly used in the literature are considered as constrained benchmark functions. Numerical results and comparisons with other state of the art stochastic algorithms are also provided. Considering both convergence and accuracy simultaneously, experimental results prove that the proposed method performs significantly better than other previous well-known metaheuristic algorithms in terms of avoiding getting stuck in local minimums, and finding the global minimum.

1. Introduction

There are countless applications for optimization in our world. Nowadays, many companies have faced problems in need of optimization. Indeed, there are many challenging problems in industry and science which are really necessary to tackle. They can be formulated as optimization problems.

We need optimization to minimize time, cost, or risk, and maximize profit, quality or efficiency. Numerous complex real-life optimization problems have emerged in many scientific fields such as engineering, economics and business [1], that cannot be solved in a reasonable amount of time and meanwhile yield a precise answer. Indeed, such problems are often highly nonlinear. Moreover, many of them include many different variables and act under complex constraints. These constraints are either in the form of simple bounds such as ranges of material properties, or in the form of nonlinear relationships such as maximum stress, maximum deflection, minimum load capacity, or geometrical configuration [2]. On the other hand, since the size of the search space increases dramatically while solving high-dimensional optimization problems, classical optimization algorithms like exhaustive search do not provide a suitable solution. Therefore, the main alternative for solving this kind of problem is using approximate algorithms.

During the 1950s and 1960s, the concept of evolution was investigated by computer scientists as an optimization tool for solving engineering problems, and later on founded a technical method called approximate algorithms. Approximate algorithms can further be divided into two classes: specific heuristics and metaheuristics. The term "heuristic" originally comes from Greek and means "to discover" and "to guide an investigation" [3]. Heuristics are techniques which seek good (near optimal) solutions at a reasonable computational cost without being able to guarantee either feasibility or optimality, or even in many cases to state how close to optimality a particular feasible solution is [4]. Specific heuristics are designed for particular problems while metaheuristics are applicable for a large variety of optimization problems, and they also accommodate to solve any optimization problem. The competence of metaheuristic algorithms can depend on the fact that they imitate the best features in nature, especially the selection of the fittest in biological systems which has evolved by natural selection over millions of years [2].

Metaheuristics are often employed to solve hard problems which need to explore a larger space. The advantage of metaheuristic algorithms is related to exploring the space efficiently without

E-mail address: salimi.hamid86@gmail.com

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being sensitive to the size of the search space. Typically, metaheuristics are based on three main purposes: solving problems faster, solving large problems and obtaining robust algorithms [1]. Moreover, ease of design and implementation along with flexibility should be the other features of these algorithms. Two important characteristics of metaheuristics are: intensification (or exploitation) and diversification (or exploration). Searching around the current best solutions, and selecting the best candidates or solutions are of the intensification properties, while diversification investigates the efficiency of the algorithm in exploring the search space often using the randomization method.

The last two decades have seen enormous development in use of metaheuristics in many science fields including artificial intelligence, computational intelligence, soft computing, mathematical programming, and operations research. Most metaheuristic algorithms are inspired by natural phenomena behaviors. Among them, Genetic Algorithm (GA) [5] established Darwin theory as one of the popular algorithms that mimic the natural evolution process. Particle Swarm Optimization (PSO) proposed by Eberhart and Kennedy [6], was inspired by social behavior of flocks of birds which are searching for their food. Developed by Karaboga, Artificial Bee Colony (ABC) simulates the foraging behavior of a bee swarm [7]. Like ABC, Ant colony (AC) is another optimization algorithm inspired by the foraging behavior of ant colonies [8]. "Every particle in the universe attracts every other particles", this is Newtonian gravity rule which Gravitational Search Algorithm (GSA) is based on [9]. Cuckoo Search (CS) [2] is another successful metaheuristic which mimics the cuckoo behavior reproduction strategy. Over the last decades, uses of metaheuristic algorithms have increased [10–17]. These algorithms are used to solve complex computational optimization problems, however, fast convergence along with accuracy is not guaranteed.

The aim of the presented work is to develop an optimization algorithm that overcomes the above shortcomings. In this paper, two novel metaheuristic algorithms based on fractal properties are presented which satisfy both fast convergence and accuracy in a few generations. The main contribution of this paper is the presentation of a new algorithm with new insight into solving optimization problems based on diffusion property turned up in fractals. These algorithms are able to achieve a solution that has the least (or at most, a small) error compared with the globally optimum solution within a minimal number of iterations, thus offering an improvement in terms of accuracy, convergence time and simplicity of operations.

In the first algorithm, each particle in the system tries to simulate the branching property of a dielectric breakdown, thus making it suitable as a search tool for solving global optimization problems. The second algorithm is the developed version of the first algorithm which can cover all disadvantages of the first algorithm. All procedures in the second algorithm can be divided into two processes called Diffusing and Updating processes. In the first process, to increase the chance of finding the global minimum, similar to the first algorithm, each particle diffuses around its current position. In the latter process, to explore the problem space efficiently, the second algorithm uses some random methods as updating processes. Since the second algorithm is more promising than the first algorithm, further experiments have been done to show the superiority of this algorithm. The main purpose of this study is to introduce a new method for tackling a variety of optimization problems with a novel perspective setting a sight for future researches. On the other hand, the algorithm is extended to solve other problems such as constrained optimization problems.

Preliminary studies show that this algorithm is very promising and could outperform existing algorithms such as PSO, CS, MCS, BSA, CME-ES, DE, GSA, ABC and other well-known metaheuristic algorithms.

The rest of paper is organized as follow: Section 2 summarizes Fractals and fractal properties. Fractal Search and Stochastic Fractal Search are described in Sections 3 and 4 respectively. Experimental results are demonstrated in Section 5, and our conclusion is made in Section 6.

2. Fractals

The property of an object or quantity which explains self-similarity on all scales, in a somewhat technical sense, is called fractal. The term of "fractal" comes from the Latin word *frāctus* which means "broken" or "fractured", and it was first used by Benoît Mandelbrot in 1975. Mandelbrot also tried to use the concept of fractal theories to describe geometric patterns in nature [18].

Developing research in this area, the example list of fractals including structures from microscopic aggregates to the cluster of galaxies has been become very long. Far-from-equilibrium growth phenomena are an important field where fractals observe, and are engaged to many fields of science and technology. Some examples for such processes include dendritic solidification in an undercooled medium, viscous fingering which is observed when a viscous fluid is injected into a more viscous one, and electrodepositing of ions onto an electrode [19].

Typically, to generate a fractal shape, some common methods such as: Iterated function systems [20], Strange attractors [21], L-systems [22], Finite subdivision rules [23] and Random fractals [24] are used. Based on the fractal characteristics, our new metaheuristic method inspires random fractals grown by Diffusion Limited Aggregation (DLA) method concept as a successful search algorithm in both accuracy and time consumption.

2.1. Random fractals

Random fractals can be generated by modifying the iteration process via stochastic rules such as Levy flight, Gaussian walks, percolation clusters, self-avoiding walks, fractal landscapes, trajectories of Brownian motion and the Brownian tree (i.e., dendritic fractals generated by modeling diffusion-limited aggregation or reaction-limited aggregation clusters) [19]. Some random fractals, such as the clusters describing a bacterial colony, can be generated by a physically motivated model called "Diffusion Limited Aggregation" (DLA) [25]. For simplicity, consider the formation of such a cluster on a plane, with the initial (seed) particle located at the origin. Other particles are then generated randomly around the original point, and cause diffusion. To simulate the diffusion process, a mathematical algorithm like random walk has been employed. The diffusing particle sticks to the seed particle which is made from it. This process is repeated until a cluster has formed. While forming the cluster, the probability of particle stuck to the end has increased comparing to the ones that penetrate the interior. Therefore, this property leads a cluster to the branch-like structure (Fig. 1).

2.2. Dielectric breakdown

Narrow discharge branchings which are frequently seen in nature are called dielectric breakdown. Study on dielectric breakdown properties shows that the branching tendency can be modeled into complicated stochastic patterns. Examples are lightning, surface discharges (Lichtenberg figures), and treeing in polymers. The global structure of branched discharges often shows a close structural similarity within a large class of discharge types but at the moment even a qualitative classification of these structures is missing. Niemeyer et al. [26] showed that branched discharges follow fractal properties, and proposed a new stochastic