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Free Search with Adaptive Differential Evolution Exploitation and Quantum-Inspired Exploration

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ABSTRACT

Recently an interesting evolutionary mechanism, sensibility, inherited from a concept model of Free Search (FS) was introduced and used for solving network problems. Unfortunately, the original FS is not easy to implement because it requires key knowledge that is not clearly defined in the existing literature to determine the neighborhood space that profoundly affects the performance of the original FS. This paper thus designs a new implementation for the concept model of FS, and proposes a new algorithm, called Free Search with Adaptive Differential Evolution Exploitation and Quantum-Inspired Exploration (ADEQFS) to address this issue. In ADEQFS, we focus on designing a new mutation strategy by employing adaptive differential evolution techniques as well as concepts and principles from real-coded quantum-inspired evolutionary algorithm. In addition, we use the crossover operation from the traditional Differential Evolution scheme to alleviate the premature convergence for the proposed algorithm. Furthermore, we employ the greedy mechanism to preserve the best solutions found at each generation. The convergence analysis of the proposed algorithm is also presented in this paper. We give the proof of convergence by using the Markov chain model. Thirty-four optimization test functions with different mathematical characteristics are employed as benchmark set to test the performance of ADEQFS. The numerical results highlight the improved convergence rate and computation reliability.

1. Introduction

Recently, the evolutionary computation algorithms have drawn a great attention to researchers. They have been introduced to solve problems in computer network (Bernardino et al., 2011; Hanning et al., 2011; Mohammad et al., 2012; Wenjia and Bo, 2011; Dhurandher et al., 2011). In 2005, Penev and Littlefair (2005) proposed a new population-based evolutionary algorithm—Free Search (FS). Compared with other population-based algorithms, the distinguished feature with regard to the conceptual model is that FS has no restriction of zero probability for the search space, and subsequently it can cope with heterogeneous optimization problems (Penev, 2009). FS can be likened to the heuristic behavior of variety of animals in nature, where they search surrounding environment with the aim of trying to find some favors (Omran and Engelbrecht, 2009). FS has attracted the attention to researchers and has been studied in the literature (Penev and Littlefair, 2005; Penev, 2009; Omran and Engelbrecht, 2009; Guang-Yu et al., 2009; Wang and Yin, 2011). FS can also be effective in the application of solving engineering problems (Hui et al., 2007; Ya-ling et al., 2009).

Artifacts in the traditional evolutionary algorithms—Genetic Algorithms, Particle Swarm Optimization, Differential Evolution, Ant Colony Optimization, and Artificial Immune System—cannot make free decisions to adjust their behaviors to their environments because these algorithms have previously modeled a system level decision process (Pomerol, 1997; Cass and De Pietro, 1998; Waltz, 2006). With this concern, FS has developed a mechanism, called sensibility, in which the individuals can make their own decisions based on various senses. An individual level decision process, therefore, is embedded in the concept model of FS, which provides individuals with an ability of artificial thinking. Nevertheless, the original FS is not easy to implement and has its own drawbacks (Omran and Engelbrecht, 2009; Guang-Yu et al., 2009; Wang and Yin, 2011): The performance of the original FS is affected by the neighborhood space which requires key knowledge that is not clearly defined in existing literature to determine it.

In this paper, an effective algorithm, Free Search with Adaptive Differential Evolution Exploitation and Quantum-Inspired Exploration (FS with ADEQ, simply denoted as ADEQFS), is proposed. ADEQFS is easy to implement with rapid convergence speed and high computation reliability. In ADEQFS, we follow the concept

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model of FS and design a new implement strategy by using concepts and principles borrowed from the adaptive differential evolution (ADE) as well as real-coded quantum-inspired evolutionary algorithm (RQEA). To be specific, the framework of concept model of FS is used to provide the individuals with sensibility in the proposed algorithm. ADE is employed as the exploitation strategy which directs individuals into promising directions more precisely. RQEA, on the other hand, is used as the exploration strategy which drives the individuals towards better solutions at a fast rate. Therefore, the combined two search strategies regarded as mutation operation, if well designed, are capable of improving the performance of proposed algorithm, balancing the search process between exploitation and exploration. Compared with the similar mutation operation in the original FS, the new designed mutation operation is easy to implement, because it does not require defining the neighborhood space. In order to alleviate the premature convergence, the crossover operation, originally from the traditional Differential Evolution, is also introduced in the proposed algorithm. Moreover, we also use the greedy mechanism to preserve the best individuals at each generation.

In addition, a theoretical analysis is also presented in this paper by using the Markov chain model to prove the convergence of ADEQFS. Thirty-four test functions are employed as benchmark set to test the performance of the proposed algorithm. These test functions have different mathematical characteristics, which include 14 different scalable functions under conditions of 30 dimensions and 100 dimensions respectively, four low dimensional functions, and two rotated and shifted functions. Simulation results show that in most situations ADEQFS is better than, or in a few cases at least comparable (in terms of convergence performance) to, Enhanced Decision Making Free Search (EDMFS), Multi-Swarm Particle Swarm Optimizer (PS^2O), Adaptive Differential Evolution with Optional External Archive (JADE with optional external archive, simply denoted as JADE), and Free Search Differential Evolution (FSDE) from the recent literature. To be specific, ADEQFS achieves the best performance on 23 test functions (f_1–f_4, f_6–f_7, f_9–f_{11}, and f_{13} with both 30 and 100 dimensions; f_{14} with 100 dimensions; f_{18} and f_{20}), and obtains comparable results in nine test functions (f_8 and f_{12} with both 30 and 100 dimensions; f_{14} with 30 dimensions; f_{15}–f_{17} and f_{19}); FSDE gets the best results in five test functions (f_5 and f_{12} with both 30 and 100 dimensions; f_8 with 30 dimensions); JADE obtains the best performance on four test functions (f_{14} with 30 dimensions, f_8 with 100 dimensions, f_{17} and f_{19}); PS^2O achieves the best results in one test function (f_{16}); EDMFS obtains the best performance on one test function (f_{15}).

The remainder of the paper is organized as follows. In Section 2, key techniques and concepts from FS, ADE, and RQEA are reviewed and discussed. The proposed algorithm, ADEQFS, and its convergence analysis are described in detail in Section 3. Experiments, results interpretation, and analysis are presented in Section 4. Finally, Section 5 gives a concise summary of our work.

The following indexes and notations will be adopted in this paper:

- i The index of vector dimension, $i=1,2,\ldots,ND$, where ND is the problem dimension.
- j The index of individual, $j=1,2,\ldots,NP$, where NP is the population size.
- k The number of selected location with pheromone, $k=1,2,\ldots,NP$.
- g The current iteration, $g=1,2,\ldots,G$, where G is the terminate iterative generation.
- LB_i,UB_i The greatest lower bound and the greatest upper bound of search space, respectively.
- $rand/rand(0,1)$ A random value between 0 and 1.

2. Related work

2.1. Free Search

Free Search (FS) is a new population-based optimization algorithm which mimics the behavior of individuals in nature. In FS, the individuals are called animals which have their own original peculiarities named sense and mobility (Penev and Littlefair, 2005). The animal can select, for start of the search walk, any location marked with pheromone, which fits its sense. In each walk, each animal can decide to go with different steps that can be large or small. During the search process, each animal also distributes a pheromone to the location. The pheromone is fully replaced with a new one after every walk around the location. The renewed pheromone can be regarded as priori knowledge which indicates the condition of searched area. The previous experience can be taken into account when each animal decides how to walk for the next, but it is not compulsory. The whole search process continues until the termination criterion is satisfied.

In the literature (Guang-Yu et al., 2009), authors proposed an algorithm, called improve Free Search (iFS), which ameliorates the neighborhood space. iFS introduces a radius contract coefficient $\rho(0 \le \rho \le 1)$, intending to change the neighborhood space during the search process. The changing neighborhood space can be regarded as a dynamical balance between exploration and exploitation. Nevertheless, this improvement might fail to have robust search ability since the neighborhood space just decreases linearly. Similar to the original FS, the performance of iFS cannot be tested easily because iFS still requires priori knowledge to set initial value of the neighborhood space. For this reason, it is infeasible to compare our proposed algorithm with FS and iFS in this paper. In the literature (Wang and Yin, 2011), authors proposed an algorithm, called EDMFS, which integrates model of FS, mutation strategy of Differential Evolution (DE), and concept of chaos theory. Compared with the original FS, EDMFS is easy to implement and does not require priori knowledge about the problem. The conducted experiments show that EDMFS generally avoids the premature convergence and outperforms traditional Particle Swarm Optimization and DE. The EDMFS, however, still consumes heavy computational cost because each animal takes different walks during the search process, and takes random steps in each walk. In the literature (Omran and Engelbrecht, 2009), authors proposed an algorithm, called FSDE, which is based on concepts from FS, DE, and opposition-based learning (OBL). Specifically, FSDE uses the framework of DE; the concepts derived from FS are employed to generate sense, with which the animal can stochastically search the marked location; OBL is used to modify the worst individual at each iteration. FSDE addresses the drawbacks of FS and DE, and its computational burden is low because FSDE inherits the advantages from DE. One drawback is that FSDE has no control parameters which render it impossible to accommodate the unique characteristics of an individual problem in achieving the best performance.

The concept model of FS consists of three major events: initialization, search, and termination. In this paper, we redesign the implementation for mutation strategy compared with the search process of the original FS, because the neighborhood space is hard to be defined between different optimization problems, considering the computational complexity. The new mutation strategy does not need to use the neighborhood space to perform the mutation operation. Instead, individuals can be mutated adaptively according to its own information which is introduced by the adaptive differential evolution and real-coded quantum-inspired evolutionary algorithm. The designed mutation operation makes the proposed algorithm converge to the global optimum at a fast speed with high reliability.