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Sampling-based adaptive bounding evolutionary algorithm for continuous optimization problems

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A B S T R A C T

This paper proposes a novel sampling-based adaptive bounding evolutionary algorithm termed SABEA that is capable of dynamically updating the search space during the evolution process for continuous optimization problems. The proposed SABEA adopts two bounding strategies, namely fitness-based bounding and probabilistic sampling-based bounding, to select a set of individuals over multiple generations and leverage the value information from these individuals to update the search space of a given problem for improving the solution accuracy and search efficiency. To evaluate the performance of this method, SABEA is applied on top of the classic differential evolution (DE) algorithm and a DE variant, and SABEA is compared to a state-of-the-art Distribution-based Adaptive Bounding Genetic Algorithm (DABGA) on a set of 27 selected benchmark functions. The results show that SABEA can be used as a complementary strategy for further enhancing the performance of existing evolutionary algorithms and it also outperforms DABGA. Finally, a practical problem, namely the model calibration for an agent-based simulation, is used to further evaluate SABEA. The results show SABEA's applicability to diverse problems and its advantages over the traditional genetic algorithm-based calibration method and DABGA.

1. Introduction

Continuous optimization problems are commonly observed in many real-world applications, such as scheduling, industrial process optimization, vehicle routing in large-scale networks and gene recognition in bioinformatics [4,7,8,23,24,26], just to name a few. To tackle these problems, evolutionary algorithms (EAs), including genetic algorithm (GA) [13], estimation of distribution algorithms (EDA) [19,39], differential evolution (DE) [14,28], particle swarm optimization (PSO) [34], Artificial Bee Colony (ABC) [1], etc., have been widely adopted. When solving continuous optimization problems using these methods, a population-based stochastic global search is performed in a search space constrained by the boundaries of the continuous variables of the problem. Candidate solutions are randomly generated within the search space and then iteratively evolved. While EA-based methods are recognized as effective approaches for continuous optimization problems, they may experience slow convergence when the search space of the problem becomes large. They may also suffer from premature convergence when solving complex multimodal problems.

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To enhance the convergence speed of EAs for solving continuous optimization problems, an effective method is to dynamically adapt the search space of problem while searching, i.e., instead of using a fixed search space throughout the search process, the boundaries of the variables are gradually updated such that new individuals can be generated within a smaller search space. As the search space is reduced during the search, this method can potentially speed up the convergence rate. Moreover, the search space updating method can be applied to many variants of EAs, including GA, DE and others. Thus, it can be used as a complementary strategy with other EAs. In this paper, we refer to an EA that uses the search space updating method as an adaptive bounding EA (ABEA).

For ABEA methods, the key question is how to effectively update the search space of a problem without missing global optimum. Several methods have been proposed in the literature. The major methods include GA with Parameter Space Size Adjustment (GAPSSA) [5], Successive Zooming GA (SZGA) [18] and Distribution-based Adaptive Bounding for GAs (DABGA) [27]. For GAPSSA, the search space is updated after each generation by narrowing the boundaries of each variable based on its average value over the whole population by a constant reduction rate. For SZGA, the search space is updated after every N_{sub} generations and the boundaries of variables are updated based on the current candidate optimal point with a fixed zooming factor. In contrast to GAPSSA and SZGA, where the reduction rate is set '*a priori*', DABGA utilizes the value distribution information of variables at the current generation to update the boundaries of each variable. DABGA has been shown to outperform GAPSSA and SZGA in terms of convergence speed and solution accuracy [27].

From the above ABEA methods, we observe some limitations. Firstly, the search space updating is based only on the information of individuals in a single generation (i.e., the generation before the search space updating). This may be problematic if the variables interact with each other. In such a case, the value of a variable in a single generation is easily affected by other interacting variables. The update of the boundaries of a variable can thus be affected by interacting variables, which can affect the search performance. Secondly, as the update of the search space relies on the current information of the variables, it is likely to be trapped into the local optima while reducing the search space. In the above methods, no explicit mechanism is provided to reduce the possibility of being trapped into the local optima. Lastly, the above methods have only been applied to the simplest form of EA, i.e., GA. The efficiency of these methods has not been tested over more advanced EAs, such as DE, and the evaluations have only conducted on relatively simple test functions.

To address the above-mentioned limitations, we propose a sampling-based adaptive bounding evolutionary algorithm (SABEA). In the proposed SABEA, the boundaries of the variables are updated based on information of individuals sampled over multiple generations. Without a fixed reduction rate, we can utilize the value information of individuals with better fitness over multiple generations to update the search space. To this end, a fitness-based bounding strategy is used to select a set of individuals with better fitness after every n_g generations. We assume that the search space constrained by these better individuals is more likely to contain the global optimum. Furthermore, we introduce an explicit mechanism to avoid the search being trapped into local optima. A probabilistic sampling-based bounding inspired by EDA [19] is adopted to randomly sample another set of individuals to improve the diversity of sampled individuals. The proposed method updates the search space based on information of individuals collected by both fitness-based bounding and probabilistic sampling-based bounding. In order to comprehensively evaluate the performance of SABEA, we apply this method on top of classic DE and two DE variants to solve a set of 27 benchmark problems taken from [37] and the CEC'05 [[31]. The experimental results clearly show the efficiency and effectiveness of SABEA for diverse problems. To demonstrate the robustness of SABEA for practical engineering problems, we further apply our method to solve the model calibration problem in an agent-based simulation. The experiments are conducted in two scenarios and the results show that the proposed method is effective at improving the convergence rate and solution accuracy.

The rest of this paper is organized as follows: Section 2 describes the related background method-DABGA. Section 3 presents the proposed SABEA. Section 4 describes the experimental studies. Section 5 concludes the paper.

2. Preliminaries

Our method is inspired and improved from the DABGA algorithm proposed by Peng et al. [27] for solving continuous optimization problems. In this section, we first introduce the continuous optimization problem and briefly describe the DABGA algorithm. Potential limitations of the DABGA algorithm are also discussed here.

The continuous optimization problem typically optimizes a real-value objective function $f(X)$. The input of $f(X)$ consists of a set of n variables $X = \{x_1, x_2, \dots, x_n\}$, where $X \in \mathbb{R}^n$. Each variable x_i is constrained by a lower bound LB_i and an upper bound UB_i, i.e., $LB_i \le x_i \le UB_i$. The upper and lower bounds of all the input variables define the search space S of the given problem, where $S \subseteq \mathbb{R}^n$. The continuous optimization problem finds the optimum X_{opt} in the search space S such that $f(X_{opt})$ is the optimal value (e.g., the global minimum) for all $X \in S$.

When applying EAs for continuous optimization problems, the boundaries of the input variables of the objective function are usually fixed during the evolution process. However, if the search space can be dynamically reduced without missing X_{opt} during the evolution, this can potentially help to speed up the convergence and improve the precision of the results. To this end, the DABGA algorithm was proposed to dynamically update the search space of the input variables for continuous optimization problems. In DABGA, the upper bound and lower bound of the ith input variable x_i of an objective function are updated according to the following rules:

$$UB_i(k+1) = \bar{x}_i(k) + b * [UB_i^{\{\beta\}}(k) - \bar{x}_i(k)], \tag{1}$$