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Ensemble of differential evolution variants

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ABSTRACT

Differential evolution (DE) is one of the most popular and efficient evolutionary algorithms for numerical optimization and it has gained much success in a series of academic benchmark competitions as well as real applications. Recently, ensemble methods receive an increasing attention in designing high-quality DE algorithms. However, previous efforts are mainly devoted to the low-level ensemble of mutation strategies of DE. This study investigates the high-level ensemble of multiple existing efficient DE variants. A multi-population based framework (MPF) is proposed to realize the **e**nsemble of multiple **DE v**ariants to derive a new algorithm named EDEV for short. EDEV consists of three highly popular and efficient DE variants, namely JADE (adaptive differential evolution with optional external archive), CoDE (differential evolution with composite trial vector generation strategies and control parameters) and EPSDE (differential evolution algorithm with ensemble of parameters and mutation strategies). The whole population of EDEV is partitioned into four subpopulations, including three indicator subpopulations with smaller size and one reward subpopulation with much larger size. Each constituent DE variant in EDEV owns an indicator subpopulation. After every predefined generations, the most efficient constituent DE variant is determined and the reward subpopulation is assigned to that best performed DE variant as an extra reward. Through this manner, the most efficient DE variant is expected to obtain the most computational resources during the optimization process. In addition, the population partition operator is triggered at every generation, which results in timely information sharing and tight cooperation among the component DE variants. Extensive experiments and comparisons have been done based on the CEC2005 and CEC2014 benchmark suit, which shows that the overall performance of EDEV is superior to several state-of-the-art peer DE variants. The success of EDEV reveals that, through an appropriate ensemble framework, different DE variants of different merits can support one another to cooperatively solve optimization problems.

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1. Introduction

Differential evolution (DE), initially introduced by Storn and Price [1], is among the most popular evolutionary algorithms (EAs) currently in use due to its simplicity and efficiency in dealing with complex optimization problems. DE is a populated stochastic search algorithm, which incorporates mutation, crossover and selection operators to move the population gradually toward the global optimum [2]. The significant difference between DE and other EAs is that it exploits solutions differences in mutation operator. DE has experienced noticeable progress since its inception [3]. Many performance enhanced DE variants has been proposed via the design of novel mutation and crossover strategies [4–10], the maintenance of population diversity [11,12], the adaptation of parameters [13–18], the hybridization with other EAs [19–22], and the intelligent combination of multiple search strategies [2,13,23,24]. DE is recognized as an efficient search engine for different optimization domains, such as constrained optimization [25], multi-objective optimization [26] and multimodal optimization [27]. In addition, DE has been widely applied to many real-world optimization problems from various fields, such as pattern recognition [28], power systems optimization [29], time series prediction [30], vehicle routing[31] and feature selection[32].

Many evidences reveal that the most appropriate mutation strategies and parameters of DE are generally different when it is applied to different optimization problems [13]. This is because different mutation and parameter settings enable DE to possess different exploitation and exploration capabilities [3]. Besides, previous studies further showed that the required mutation strategies and parameters may even vary during the evolution process when solving one optimization problem [24]. Nevertheless, traditional trial-and-error approaches for configuring strategies and parameters are usually tedious, time-consuming and ineffective [23]. In response to this challenge, several approaches have been presented for intelligent mutation strategy ensemble and automated parameter adaptation [2,13,23,24,27,33,34]. Qin et al. [13] proposed a self-adaptive DE algorithm (SaDE) in which the mutation strategies and the respective control parameter are self-adapted based on their previous experiences of generating promising solutions. The scale factor, F was randomly generated with a mean and standard deviation of 0.5 and 0.3, respectively. Gong et al. [35] presented two DE variants with two adaptive strategy selection techniques, namely the Probability Matching and Adaptive Pursuit to choose appropriate mutation strategies with certain probabilities. The selection probabilities of mutation strategies are determined by their respective previous search performance that is evaluated by a credit assignment technique. In [23], the authors proposed a DE algorithm with an ensemble of mutation strategies and parameter values (EPSDE) which consists of a pool of mutation and crossover strategies and their associated parameter values. Gong et al. [36] proposed a cheap surrogate model for the ensemble of multiple search operators in evolutionary optimization. In their approach, a set of candidate offspring solutions are generated by using the multiple offspring reproduction operators and the best one according to the surrogate model is chosen as the offspring solution. Zhao et al. proposed an ensemble of different neighborhood sizes with online self-adaptation to enhance the multiobjective evolutionary algorithm based on decomposition [37].

From a higher level perspective, different DE variants exhibit different capabilities in solving different optimization problems. Actually, the No-free-lunch theorem tells that all search algorithms will averagely own the same performance when they are applied to all potential optimization problems, that is to say, theoretically, there will not exist a general optimization algorithm being superior to all others [38,39]. Many popular and efficient DE variants have been put forward during last two decades. There is no doubt that these DE variants have their respective advantages in dealing with different optimization problems. As a result, it is meaningful yet challenging to make full use of the advantages of different DE variants to derive an even better DE.

In reality, the idea of mixing multiple search components or EAs has attracted much attention from researchers for a long time. In addition to ensemble algorithm, some other related concepts have been presented, such as memetic algorithm [40], hybrid algorithm [41–43], hyper-heuristics [44,45] and algorithm portfolios [46].

In this study, we focus on the high-level ensemble of different DE variants. A multi-population based framework (MPF) is proposed to combine multiple DE variants together and allocate computational resources to constituent DE variants dynamically in terms of their respective historical performance. This framework is inspired from our previous work [24], in which an ensemble of multiple mutation strategies of DE was implemented to derive a new DE variant named MPEDE, which showed very competitive performance. Two types of subpopulations are included in the MPF, namely, indicator subpopulation and reward subpopulation. Three highly popular and efficient DE variants, including JADE [15], EPSDE [23] and CoDE [2], are incorporated into MPF. Each of these three constituent DE variants has an indicator subpopulation. That is to say, there are total three indicator subpopulations in MPF. In addition, one reward subpopulation is contained in MPF (the overall population minus the three indicator subpopulations). Generally, the sizes of the indicator subpopulations are equal and much smaller than the reward subpopulation. During the evolutionary process, after every certain number of generations, the best performed constituent DE variant is determined in terms of the performance measured by the fitness improvements divided by consumed function evaluations. The reward subpopulation then is assigned to the current best performed DE variant, which is supposed to be able to continue the performance dominance in the near future evolutionary process. The best performing DE variant determination and the reward subpopulation reallocation operators are executed periodically. Hence, MPF ensures that the best DE variant can gain the most computational resources timely.

The paper is structured as follows. Section 2 reviews related works. Section 3 introduces the proposed ensemble of DE variants, including its framework, constituent DE variants and exploration-exploitation mechanisms. Section 4 reports related experimental studies. Section 5 concludes this work.