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A novel hybrid multi-objective immune algorithm with adaptive differential evolution

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A B S T R A C T

In this paper, we propose a novel hybrid multi-objective immune algorithm with adaptive differential evolution, named ADE-MOIA, in which the introduction of differential evolution (DE) into multi-objective immune algorithm (MOIA) combines their respective advantages and thus enhances the robustness to solve various kinds of MOPs. In ADE-MOIA, in order to effectively cooperate DE with MOIA, we present a novel adaptive DE operator, which includes a suitable parent selection strategy and a novel adaptive parameter control approach. When performing DE operation, two parents are respectively picked from the current evolved and dominated population in order to provide a correct evolutionary direction. Moreover, based on the evolutionary progress and the success rate of offspring, the crossover rate and scaling factor in DE operator are adaptively varied for each individual. The proposed adaptive DE operator is able to improve both of the convergence speed and population diversity, which are validated by the experimental studies. When comparing ADE-MOIA with several nature-inspired heuristic algorithms, such as NSGA-II, SPEA2, AbYSS, MOEA/D-DE, MIMO and D^2MOPSO, simulations show that ADE-MOIA performs better on most of 21 well-known benchmark problems.

1. Introduction

Optimization problems widely exist in many domains of scientific research and engineering application [1–4]. Based on the number of objectives needed to be optimized, they are generally classified into two categories, such as single-objective optimization problems (SOPs) and multi-objective optimization problems (MOPs). Generally, MOPs bring more challenges as they are aimed at optimizing several conflicting objectives simultaneously, while SOPs only locate a global optimal value. Due to the complex landscape in decision and objective spaces of MOPs, it is practically impossible for traditional deterministic approaches to travel the entire solution space and find a satisfactory result within a limited time. As a result, evolutionary algorithms (EAs) are presented for solving MOPs, which demonstrate the excellent global search capability in finding optimal solution set [5,6]. The ability to handle complex MOPs that are characterized with discontinuities, multimodality, disjoint feasible spaces and noisy function evaluations, reinforces the potential effectiveness of multi-objective EAs (MOEAs) [7,8].

The first reported literature of MOEAs may be the vector evaluated genetic algorithm (VEGA) in mid-1980s [9]. After that, MOEAs attract more and more interests of researchers and numbers of various MOEAs are presented. The first generation of MOEAs published around 1990s mostly adopted the Pareto-rank based selection and fitness sharing, the representatives of which include multi-objective genetic algorithm (MOGA) [10], niched Pareto genetic algorithm (NPGA) [11] and non-dominated sorting genetic algorithm (NSGA) [12]. In 2000s, the second generation of MOEAs was designed based on the elitist selection strategy, such as strength Pareto evolutionary algorithm (SPEA) [13] and its improved version (SPEA2) [14], Pareto envelop-based selection algorithm (PESA) [15], and a fast non-dominated sorting genetic algorithm (NSGA-II) [16]. Recently, as more and more heuristic algorithms including scatter search [17], simulated annealing [18], particle swarm optimization [19], ant colony optimization [20], differential evolution [21] and immune algorithm [22], are presented, it is found that multiple heuristic algorithms can be hybridized to achieve stronger search capabilities [23–25]. This is realized by combining the advantages of various heuristic algorithms to overcome the natural weakness of each algorithm. For example, an archive-based hybrid scatter search algorithm (AbYSS) is proposed [23], which embeds the mutation and crossover operators of EAs into the framework of scatter search. The experimental studies show that this hybrid approach obviously outperforms the state-of-the-art algorithms, such as SPEA2 and NSGA-II. A novel hybrid multi-objective evolutionary algorithm [24] is designed for real-valued MOPs by combining the concepts of personal best and global best in particle swarm optimization into MOEAs. Multiple crossover operators are also adopted here to

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enhance its global search capability. In [25], a multi-objective particle swarm optimizer based on decomposition and dominance (D^2MOPSO) is presented, which incorporates the dominance relationship with the decomposition approach. The improved version of D^2MOPSO is also proposed by the same authors with the introduction of a new mechanism for leaders' selection and a new archiving technique [26]. These new features facilitate the attaining of better diversity and coverage in both objective and solution spaces.

Differential evolution (DE) algorithm is a simple and efficient random search technology that is mainly used for continuous global optimization problems [27,28]. Because of its excellent global search ability and easy implementation, DE is recently investigated to mix with MOEAs for compensating the defects of lacking diversity in some MOEAs [29–34]. In [29], a differential evolution algorithm for multi-objective optimization with rough sets (DEMORS) theory is proposed, which uses the concept of ε-dominance to keep the population diversity. Two stages are sequentially performed, in which the first stage generates an initial population close to the true Pareto front by using the multi-objective version of DE and the second stage exploits the rough sets theory to further improve the convergence and the diversity of population founded in the first stage. DEMORS is justified to outperform some state-of-the-art MOEAs and extended to solve the complex constrained MOPs in [30]. A novel multi-objective evolutionary algorithm based on decomposition (MOEA/D) is designed by Zhang and Li [31], which decomposes MOPs into multiple SOPs using the weighted aggregation of each objective. A basic DE operator is adopted to replace the simulated binary crossover operator and the experimental studies confirm the advantages of DE when handling some complex MOPs with variable linkages in decision space [32]. Recently, an adaptive differential evolution for MOEA/D (ADEMO/D) is reported in [33], which introduces the adaptive control strategy of SaDE [28] into the framework of MOEA/D. The improved version of ADEMO/D [34] replaces the self-adaptive DE strategy with a novel adaptive selection strategy (AdapSS) [27].

On the other hand, artificial immune system (AIS) is a new developing heuristic algorithm imitating the information processing mechanism of biological immune system [35], which has found numbers of applications in the fields of computer security [36], optimization [37], and anomaly detection [38]. Especially, immune algorithm has been successfully applied for MOPs and shown pretty promising performance in accelerating the convergence speed and maintaining the population diversity [37]. However, when dealing with some complex MOPs, such as DTLZ and WFG test problems [39,40], it is quite difficult to fast approach the true Pareto front in limited generations. As the previous studies have shown that the hybridization of MOEAs with DE is especially effective for solving some complex MOPs, it is reasonable to believe that the embedment of DE into multi-objective immune algorithms (MOIAs) is promising. Especially, MOIAs may suffer from the lack of population diversity due to the elitist clonal selection principle. The global search capability of DE operator can repair that defect and enhance the robustness of MOIAs to handle various kinds of MOPs. However, to the best of our knowledge, this integration of MOIAs with DE is rarely investigated. Therefore, in this paper, we propose a novel multi-objective immune algorithm with adaptive DE (ADE-MOIA), where the adaptive DE (ADE) operator substantially improves both of the convergence speed and population diversity. The ADE operation is designed by a suitable parent selection strategy and a novel adaptive parameter control method. By dividing the population into a dominated subpopulation and a non-dominated subpopulation, three parents to run DE operator are respectively chosen from the corresponding subpopulations. The difference between the dominated and non-dominated parents may provide a correct evolutionary direction in DE. Besides that, as the choice of systematic parameters in DE has great impact on the optimization performance, an adaptive control approach is presented to tune the crossover rate (CR) and scaling factor (F), which is aimed at decreasing the influence of parameter settings and enhancing its robustness. In our ADE operation, CR is gradually changed with the evolutionary process while F is adaptively modified for each individual based on the success rate of offspring. The advantage of the proposed ADE operator is verified by the experimental studies. To investigate the performance of ADE-MOIA, 21 well-known benchmark problems such as ZDT problems [41], WFG problems [40] and DTLZ problems [39], are used. When compared with various nature-inspired heuristic algorithms, such as NSGA-II [16], SPEA2 [14], AbYSS [23], MOEA/D-DE [32], MIMO [37] and D^2MOPSO [26], ADE-MOIA performs best on most of benchmark problems.

The remainder of this paper is organized as follows. Section 2 describes the related background, such as MOPs, AIS and related work of immune algorithm. The realization of ADE-MOIA is introduced in Section 3, where the cloning, ADE, perturbance and archive update operators are respectively described in detail. The experimental studies are conducted in Section 4, which gives a comparative study among ADE-MOIA and various nature-inspired heuristic algorithms. Moreover, the advantage of ADE operator is analyzed and its effectiveness is confirmed by the experimental results. At last, the conclusions are summarized in Section 5.

2. Related background

2.1. Multi-objective optimization problems

There exist many MOPs in various practical applications, which may need to handle constraints and optimize multiple conflicting objectives simultaneously. Without loss of generality, the mathematical description of MOPs for minimization can be expressed as follows:

$$\begin{aligned} &\text{Minimize } f(x) = \{f_1(x), f_2(x), ..., f_m(x)\} \\ &\quad \text{s.t.}: \; g_i(x) \le 0, \; i = 1, 2, ..., q \\ &\quad h_j(x) = 0, \; j = 1, 2, ..., p \end{aligned} \tag{1}$$

where $x = (x_1, x_2, ..., x_n) \in \Omega$ is a decision vector with n dimensions, Ω is the decision space, m is the number of objectives, $g_i(x)$ $(i = 1, 2, ..., q)$ are q inequality constraints and $h_j(x)$ $(j = 1, 2, ..., p)$ are p equality constraints.

The goal of MOPs is to minimize all the objective functions in Eq. (1) and the concepts of Pareto optimum theory [42] are important for MOPs, which are described as follows.

Definition 1. (Pareto-dominance): A decision variable vector x is said to dominate another decision variable vector y (noted as $x \succ y$) if and only if

$$(\forall i \in \{1, 2, ..., m\} : f_i(x) \le f_i(y)) \wedge (\exists j \in \{1, 2, ..., m\} : f_j(x) < f_j(y)) \tag{2}$$

Definition 2. (Pareto-optimal): A solution x is said to be Pareto-optimal if and only if

$$\neg \exists y \in \Omega : y \succ x \tag{3}$$

Definition 3. (Pareto-optimal set): The set PS includes all the Pareto-optimal solutions, as defined by

$$PS = \{x \mid \neg \exists y \in \Omega : y \succ x\} \tag{4}$$

Definition 4. (Pareto-optimal front): The set PF includes the values of all the objective functions corresponding to the Pareto-optimal