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A novel micro-population immune multiobjective optimization algorithm

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ABSTRACT

In this paper, we present a novel immune multiobjective optimization algorithm based on micro-population, which adopts a novel adaptive mutation operator for local search and an efficient fine-grained selection operator for archive update. With the external archive for storing nondominated individuals, the population diversity can be well preserved using an efficient fine-grained selection procedure performed on the micro-population. The adaptive mutation operator is executed according to the fitness values, which promotes to use relatively large steps for boundary and less-crowded individuals in high probability. Therefore, the exploratory capabilities are enhanced. When comparing the proposed algorithm with a recently proposed immune multiobjective algorithm and a scatter search multiobjective algorithm in various benchmark functions, simulations show that the proposed algorithm not only improves convergence ability but also preserves population diversity adequately in most cases.

1. Introduction

In many science and engineering applications, it is common to encounter the problems of optimizing many objectives simultaneously, known as multiobjective optimization problems (MOPs). Without loss of generality, the mathematical model of MOPs can be formulated for minimization problems as follows:

Finding a vector $x=(x_1,x_2,\ldots,x_n)\in\Omega\subset\mathbb{R}^n$ for

$$\text{Min } F(x)=(f_1(x),f_2(x),\ldots,f_m(x))^T \tag{1}$$

where m is the number of objectives; $\mathbb{R}^n$ defines the vector space of decision variables and Ω is the feasible region bounded in $\mathbb{R}^n$, which satisfies a set of k $(k\geq 0)$ additional inequality constraints and $l(l\geq 0)$ additional equality constraints: $g_i(x)\leq 0(i=1,2,\ldots,k)$ and $h_j(x)=0(j=1,2,\ldots,l)$, respectively. Since the measures of objectives often conflict with each other, no single solution can optimize all the objectives simultaneously. The best tradeoff among the objectives is a set of solutions known as *Pareto-optimal solutions*, each of which is nondominated when considering all the objectives. This set is known as *Pareto-optimal set* and the corresponding objective vectors are known as *Pareto-optimal front*. The goal of MOPs is to find a set of representative solutions, which are distributed uniformly and as close to the true Pareto-optimal front as possible.

Generally, as the expensive computational time is needed for computing the objective functions and constraints in many practical MOPs, traditional deterministic techniques are not applicable in this instance and stochastic approaches seem to be particularly suitable for MOPs. Specifically, Evolutionary Algorithms (EAs) have been demonstrated to be an effective and efficient tool for MOPs as they can process a set of solutions simultaneously in a single run. The ability to handle complex problems, involving features such as discontinuities, multimodality, disjoint feasible spaces and noisy function evaluations, reinforces the potential effectiveness of EAs in MOPs [1]. Since the first reported approaches such as the Vector Evaluated Genetic Algorithm (VEGA) [2], the genetic search strategies algorithm [3], the Nondominated Sorting Genetic Algorithm (NSGA) [4] and the genetic algorithm with a rank-based fitness assignment method [5], the growing interest of using EAs in MOPs has given rise to many state-of-the-art algorithms, *i.e.*, NSGA-II [6], SPEA-2 [7] and PESA-II [8]. Recently, researchers have been working on designing specific operators to further improve the optimization performance of MOPs, such as an adaptive mutation operator and an enhanced exploration strategy [9,10], an outranking-based dominance [11] and a convergence acceleration operator [12].

Inspired by the information processing capacity of the Human Immune System that is a highly evolved, parallel and distributed adaptive system, Artificial Immune Systems (AIS) gain more and more attentions in many research fields such as computer security, optimization, anomaly detection, etc. [13]. Particularly, AIS were extended for solving MOPs in recent years. There are two attempts of using AIS in MOPs. The first attempt considers

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the use of AIS as a tool to improve the performance of the other bio-inspired algorithms [14–16]. The second one designs the targeted Immune Multiobjective Optimization Algorithms (IMOAs) directly based on the principle of AIS. For example, IMOAs based on the clonal selection principle include a Multi-objective Immune System Algorithm (MISA) [17,18], an Immune Dominance Clonal Multiobjective Algorithm (IDCMA) [19] and the improved version named as Nondominated Neighbor-based Immune Algorithm (NNIA) [20]; IMOAs based on artificial immune network include a Vector Artificial Immune System (VAIS) [21] and a novel weight-based multiobjective artificial immune system [22]; IMOAs based on the characteristics of AIS include a dynamic immune multiobjective algorithm [23,24] and a multiple-affinity immune multiobjective algorithm [25].

Recently, we proposed a Hybrid Immune Multiobjective Optimization (HIMO) algorithm based on the clonal selection principle, in which a hybrid mutation operator was presented with the combination of Gaussian and polynomial mutations [26]. Based on HIMO, we propose a novel Micro-Population Immune Multiobjective Optimization algorithm (MIMO), the improvements of which are a novel adaptive mutation operator for local search and an efficient fine-grained selection operator for selecting nondominated individuals. Without switching between the two mutations, the adaptive mutation operator is executed based on the fitness value, which encourages using relatively large steps for boundary and less-crowded individuals with high probability in order to enhance exploratory capabilities. The fine-grained selection operator can preserve population diversity well with minor additional computation using an efficient refined selection procedure when selecting individuals from a micro-population to preserve in the external archive. By this means, the proposed operators improve both the convergence and the diversity. When MIMO is compared with HIMO [26] and a scatter search multiobjective algorithm (AbYSS) [27] in various benchmark functions, simulations show that the proposed algorithm has outstanding optimization performance in most cases.

This paper is organized as follows. In Section 2, we introduce the related background of AIS and some related IMOA. Section 3 describes the procedures of MIMO, *i.e.*, proportional cloning, simulated binary crossover, adaptive mutation and fine-grained selection operators. Complexity analysis is also given in this section. Section 4 shows the simulation results of MIMO, HIMO and AbYSS. In addition, the effectiveness of the proposed operators is also investigated in this section. Finally, conclusions are given in Section 5.

2. Related background

2.1. Immune system

The human immune system can eliminate the intruding antigens by adapting its B-cells, which includes the processes known as clonal selection and affinity maturation by hypermutation. After that, some specific antibodies are long lived as memory cells in order to prevent the reinfection of the previous intruding antigens. Clonal selection principle explains the basic features of an adaptive immune response to an antigenic stimulus, which establishes the idea that only those cells that recognize the antigens are selected to proliferate and go through an affinity maturation process in order to improve their affinity for the selective antigens [28]. In multiobjective immune algorithm, the problem and its constraints can be seen as the antigen. The candidate solutions of the problem can be seen as antibodies. Especially for MOPs in Eq. (1), a solution vector $x=(x_1, x_2,\dots,x_n)$ is taken as an antibody. A population is made up by set of antibodies. With the definition of Pareto dominance, an antibody is called as a nondominated antibody when there are no other antibodies in population, which are better than it in all the objectives.

2.2. Related work

The first reported approach using AIS for MOPs was proposed by Yoo and Hajela [29], which uses AIS to modify the fitness assignment of a genetic algorithm. The characteristic feature of biological immune systems that allows for the generation of multiple specialist antibodies is effective to facilitate the generation of the Pareto-optimal front. Coello Coello and Cruz proposed a Multiobjective Immune System Algorithm (MISA) [17] based on the clonal selection principle, modeling the fact that only the highest affinity antibodies to the antigens will proliferate. An external memory is used to store the nondominated antibodies found in evolutionary process. The performance of MISA is further improved with two types of mutations: uniform mutation is applied to the clones and non-uniform mutation is applied to the "not so good" antibodies [18]. Freschi and Repetto proposed a Vector Artificial Immune System (VAIS) for MOPs based on the artificial immune network [21], in which similar antibodies are suppressed. Jiao et al. proposed an Immune Dominance Clonal Multiobjective Algorithm (IDCMA), which adopts binary string representation and the Ab–Ab affinity based selection on dominated individuals [19]. The improved version of IDCMA is Nondominated Neighbor-based Immune Algorithm (NNIA) proposed by Gong et al. with real-coded representation, a new selection technique and population maintenance strategy [20]. Zhang proposed a dynamic immune multiobjective algorithm for constrained MOPs based on the simple interactive metaphors between antibody population and multiple antigens [23], which was extended for application in greenhouse control [24]. Hu proposed a multiobjective immune algorithm based on a multiple-affinity model, in which six affinity assignments were proposed. Immune operators such as clonal proliferation, hypermutation and immune suppression are performed according to specific affinity measures, which proliferate the superiors and suppress the inferiors [25]. Gao and Wang proposed a novel weight-based multiobjective artificial immune system [22], which follows the elementary structure of opt-aiNET [30]. A randomly weighted sum of multiple objectives is used as a fitness function and a new truncation algorithm with similar individuals is presented in order to eliminate similar individuals in memory. Therefore, it has low computation complexity and can obtain a well-distributed Pareto-optimal approximation set.

In [26], we proposed HIMO for MOPs based on the clonal selection principle. In HIMO, a hybrid mutation is proposed with the combination of Gaussian and polynomial mutations. It adopts an adaptive switching parameter to control the mutation process, which uses relatively large steps in high probability for boundary individuals and less-crowded individuals. Besides that, nondominated neighbor-based selection proposed by Gong et al. [20] is adopted in HIMO to encourage exploring the less-crowed regions. However, we found that the performance of nondominated neighbor-based selection can be improved by a more refined procedure and the switch between two mutations can be replaced by an adaptive mutation operator in order to enhance its exploratory capacity. So we modified HIMO using an adaptive mutation operator, a fine-grained selection operator and micro-population evolution strategy, the MIMO was proposed accordingly.