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WBMOAIS: A novel artificial immune system for multiobjective optimization

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ABSTRACT

This study presents a novel weight-based multiobjective artificial immune system (WBMOAIS) based on opt-aiNET, the artificial immune system algorithm for multi-modal optimization. The proposed algorithm follows the elementary structure of opt-aiNET, but has the following distinct characteristics: (1) a randomly weighted sum of multiple objectives is used as a fitness function. The fitness assignment has a much lower computational complexity than that based on Pareto ranking, (2) the individuals of the population are chosen from the memory, which is a set of elite solutions, and a local search procedure is utilized to facilitate the exploitation of the search space, and (3) in addition to the clonal suppression algorithm similar to that used in opt-aiNET, a new truncation algorithm with similar individuals (TASI) is presented in order to eliminate similar individuals in memory and obtain a well-distributed spread of non-dominated solutions. The proposed algorithm, WBMOAIS, is compared with the vector immune algorithm (VIS) and the elitist non-dominated sorting genetic system (NSGA-II) that are representative of the state-of-the-art in multiobjective optimization metaheuristics. Simulation results on seven standard problems (ZDT6, SCH2, DEB, KUR, POL, FON, and VNT) show WBMOAIS outperforms VIS and NSGA-II and can become a valid alternative to standard algorithms for solving multiobjective optimization problems.

1. Introduction

Many real-world problems involve the simultaneous optimization of various and often conflicting objectives. Often, there is no single optimal solution, but rather a set of alternative solutions. These solutions are optimal in the wider sense that no other solutions in the search space are superior to them when all objectives are considered. They are known as Pareto-optimal solutions.

For multiobjective optimization problems (MOOPs), evolutionary algorithms (EAs) in general have been demonstrated to be effective and efficient tools for finding approximations of the Pareto front. For a good overview of the current state-of-the-art in multiobjective evolutionary algorithms (MOEAs), we refer the reader to some of the main books in the field [16,30].

During the last decade, based on principles of the immune system, a new paradigm, called artificial immune system (AIS), has been employed for developing interesting algorithms in many fields such as pattern recognition, computer defense, optimization, and others [17,31]. However, very few direct approaches to MOOPs using AIS have been proposed, and most of the existing work considers the use of AIS as a tool for keeping diversity in the population of a genetic algorithm (GA) [4] or handling constraints in EAs [12]. The first reported approach which uses AIS for solving MOOPs was proposed by Yoo and Hajela [9]. In their approach, AIS is used for modifying the fitness values of a GA. Although Yoo and Hajela's algorithm cannot be considered a true multiobjective artificial immune system (MOAIS), it is a pioneer in using AIS ideas in MOOPs. Coello Coello and Cruz Cortés in 2002 presented a MOAIS based on the clonal selection theory [18]. The algorithm, called the multiobjective immune system algorithm (MISA), can be considered the really first attempt to solve MOOPs directly with AIS. The performance of MISA has been improved in further work of the same authors in 2005 [23]. In the following year, based on opt-aiNET, the multi-modal AIS optimization algorithm proposed by Castro and Timmis [19], Freschi and Repetto presented a vector immune system (VIS) [26]. In the Freschi and Repetto study, VIS follows the elementary structure of the opt-aiNET optimization algorithm, and the differences between opt-aiNET and VIS are very few. Besides them, many approaches using the AIS metaphor have been presented in recent years. Representatives of them include Luh and Chueh's multiobjective immune algorithm (MOCSA) [21,22], the immune dominance clonal multi-objective algorithm (IDCMA) presented by Jiao et al. [24,25], the immune forgetting multiobjective optimization algorithm (IFMOA) suggested by Wang et al. [27], the adaptive clonal selection algorithm

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for multiobjective optimization (ACSAMO) proposed by Wang and Mahfouf [28], and Zhang's multiobjective optimization immune algorithm in dynamic environments [29].

In this study, like VIS, we follow the elementary structure of opt-aiNET and present a novel multiobjective artificial immune algorithm, which is a metaheuristic algorithm for multiobjective optimization. Compared to the other MOAIS based on opt-aiNET, our proposed algorithm, called the weight-based multibojective artificial immune system (WBMOAIS), has its distinct features. Firstly, WBMOAIS uses a random weighted sum of multiple objectives as a fitness function. The fitness function is utilized by a local search algorithm to improve each clonal solution. Secondly, we define a term called similar individuals. Based on the definition, a new diversity approach, named truncation algorithm with similar individuals (TASI) is presented. Here we use two diversity approaches together, TASI and the clonal suppression algorithm which is similar to that used in opt-aiNET, to eliminate similar cells in memory. Furthermore, TASI is used as the main diversity approach in order to obtain a better distribution of Pareto-optimal solutions. In addition, the individuals of the population are chosen from the memory, and a local search procedure is utilized to improve the quality of the population. Our proposed algorithm, WBMOAIS, is tested on seven standard problems and compared with VIS and NSGA-II [20].

The remainder of this paper is organized as follows. In the second section, the MOOP and some related terms are described. In the third section, we present a novel weight-based multiobjective artificial immune system, and propose a new diversity operator: TASI. Besides, a local search algorithm and the clonal suppression algorithm are also discussed. Numerical experiments on seven test problems are presented in the fourth section. The fifth section contains our conclusions and points to our future research direction.

2. Multiobjective optimization problem

A MOOP has a number of objective functions which are to be minimized or maximized. As in the single-objective optimization problem, here too the problem usually has a number of constraints which any feasible solution must satisfy. Without loss of generality, here the minimization for each objective is considered. In the following, we state the MOOP in its general form:

$$\text{Minimize } f_i(\mathbf{x}), \quad i=1,2,\ldots,m, \tag{1}$$

where each f_i, $1 \leqslant i \leqslant m$, is an objective function, $\mathbf{x}=[x_1,x_2,\ldots,x_n]^T \in \Omega$ is the vector of decision variables and $\Omega \subseteq \mathscr{R}^n$ is the domain of the variables, defined by their lower and upper bounds

$$x_i^L \leqslant x_i \leqslant x_i^U, \quad i=1,2,\ldots,n. \tag{2}$$

The feasible set $\mathscr{F} \subset \Omega$ can be restricted by inequality and equality constraints

$$g_j(\mathbf{x}) \geqslant 0, \quad j=1,2,\ldots,J, \tag{3}$$
$$h_k(\mathbf{x}) = 0, \quad k=1,2,\ldots,K. \tag{4}$$

Next, we assume that the vector $\mathbf{f}(\mathbf{x})=[f_1(\mathbf{x}),f_2(\mathbf{x}),\ldots,f_m(\mathbf{x})]^T$ and give several definitions related to MOOPs.

Definition 1 (*Pareto dominance*). A feasible decision vector $\mathbf{x}_p$ is said to dominate another feasible vector $\mathbf{x}_q$ (denoted by $\mathbf{x}_p \prec \mathbf{x}_q$), if both conditions (i) and (ii) are true.

(i) $\mathbf{x}_p$ is no worse than $\mathbf{x}_q$ in all objectives

$$\forall i=1,2,\ldots,m, \quad f_i(\mathbf{x}_p) \leqslant f_i(\mathbf{x}_q). \tag{5}$$

(ii) $\mathbf{x}_p$ is strictly better than $\mathbf{x}_q$ in at least one objective

$$\exists i=1,2,\ldots,m, \quad f_i(\mathbf{x}_p) < f_i(\mathbf{x}_q). \tag{6}$$

If there is no solution $\mathbf{x}_p$ that dominates $\mathbf{x}_q$, then $\mathbf{x}_q$ is a Pareto-optimal solution.

Definition 2 (*Pareto-optimal set*). For a given MOOP, the Pareto-optimal set, $\mathscr{PS}$, is defined as

$$\mathscr{PS} := \{\mathbf{x} \in \mathscr{F} \mid \neg\exists \mathbf{x}^* \in \mathscr{F}, \mathbf{x}^* \prec \mathbf{x}\}. \tag{7}$$

Definition 3 (*Pareto front*). For a given MOOP and the Pareto-optimal set, the Pareto front, $\mathscr{PF}$, is defined as

$$\mathscr{PF} := \{\mathbf{f}(\mathbf{x}) \mid \mathbf{x} \in \mathscr{PS}\}. \tag{8}$$

Definition 4 (*Non-dominated set*). Among a set of solutions P, the non-dominated set of solutions P^* is composed of solutions that are not dominated by any other solution of the set P.

From Definitions 2 and 4, it is clear that a Pareto-optimal set is always a non-dominated set. But there may exist non-dominated sets containing some Pareto-optimal solutions and some non-Pareto-optimal solutions. Thus it is important to realize that the non-dominated solutions found by an optimization algorithm are not certain to be able to represent the true Pareto-optimal set. Therefore, in this study the actual Pareto front, termed $\mathscr{PF}_{\text{true}}$, is distinguished from the final set of non-dominated solutions returned by a MOEA, termed $\mathscr{PF}_{\text{known}}$ as remarked by Van Veldhuizen and Lamont [13].

3. Algorithm

3.1. Opt-aiNET optimization algorithm

In recent years, some different AIS-based algorithms have been developed. One of the popular approaches is the clonal selection algorithm presented by de Castro and Von Zuben [17]. The clonal selection algorithm has shown a great ability for searching multiple optimal solutions. In 2002, de Castro and Timmis enhanced the clonal selection algorithm by combining it with immune network theory developed by Jerne [1], and furthermore proposed a new algorithm called opt-aiNET. The framework of the opt-aiNET algorithm is shown in Fig. 1. From Fig. 1, it can be observed that the behavior of opt-aiNET can be explained in a simple form. The opt-aiNET algorithm is structured into two nested levels. The inner level (exploitation of the fitness landscape) takes into account computing the affinity relations, stimulating the most promising cells, while the outer level (exploration of the fitness landscape) manages the network of cells of the system, deleting similar ones and preserving the most promising ones into memory. The cardinality of the population can be fixed or dynamic. However, new cells are generated throughout the process in order to explore as much as possible the solution space. Details of the multi-modal, single-objective optimization algorithm are provided by de Castro and Timmis [19].

3.2. The proposed algorithm

In this section, we will present a novel multiobjective optimization algorithm based on the opt-aiNET optimization approach. The algorithm, called the weight-based multiobjective artificial immune system, follows the structure of opt-aiNET and uses a randomly weighted sum of multiple objectives as a fitness function. The main framework is shown in Fig. 2.