Information Sciences 430–431 (2018) 46–64

Contents lists available at ScienceDirect

Information Sciences

journal homepage: www.elsevier.com/locate/ins

An adaptive immune-inspired multi-objective algorithm with multiple differential evolution strategies

Qiuzhen Lin[a], Yueping Ma[a], Jianyong Chen[a], Qingling Zhu[a], Carlos A. Coello Coello[b], Ka-Chun Wong[c], Fei Chen[a,*]

[a] College of Computer Science and Software Engineering, Shenzhen University, Shenzhen, PR China
[b] CINVESTAV-IPN, Department of Computer Science, Mexico, D.F. 07360, Mexico
[c] Department of Computer Science, City University of Hong Kong, Hong Kong, PR China

ARTICLE INFO

Article history:
Received 3 February 2017
Revised 1 November 2017
Accepted 16 November 2017
Available online 20 November 2017

Keywords:
Multi-objective optimization
Immune algorithm
Differential evolution
Adaptive strategy selection

ABSTRACT

Most multi-objective immune algorithms (MOIAs) adopt clonal selection to speed up convergence, as this operator only clones the best individuals during the search process. However, this approach somehow deteriorates the population diversity, which may cause a MOIA to be trapped in a local optimum and could also lead to premature convergence when tackling some complicated multi-objective optimization problems (MOPs). In order to overcome this problem, an adaptive immune-inspired multi-objective algorithm (AIMA) is presented in this paper, in which multiple differential evolution (DE) strategies having distinct advantages are embedded into a conventional MOIA. Our proposed approach strengthens the exploration capabilities of a MOIA while also improving its population diversity. At each generation, based on the current search stage, an adaptive selection method is designed to choose an appropriate DE strategy for evolution. The core idea is to effectively combine the advantages of three DE strategies when solving different MOPs. A number of comparative experiments are conducted on the well-known and frequently-used WFG and DTLZ test problems. Our experimental results validate the superiority of our proposed AIMA, as it performs better than some state-of-the-art multi-objective optimization algorithms and some state-of-the-art MOIAs.

1. Introduction

Optimization problems widely exist in scientific research and engineering applications. Based on the number of objectives to be optimized, they are generally classified into single-objective optimization problems (SOPs) and multi-objective optimization problems (MOPs). This paper focuses on tackling MOPs, which give rise to several challenges due to the aim of optimizing several (often conflicting) objectives simultaneously. There is a wide variety of real-world MOPs, such as route planning [36], job shop scheduling [18], and data classification [1]. Due to the conflict among the objectives, the optimization of a MOP generates a set of solutions representing the best possible trade-off among all the objectives, which compose the so-called Pareto-optimal set (***PS***). The corresponding mapping of ***PS*** in objective space is termed Pareto-optimal front (***PF***). Without any further preference information, the goal of multi-objective optimization is to produce a set of solutions, which approximate the true ***PF*** as close as possible and are distributed along the true ***PF*** as uniformly as possible.

* Corresponding author.
E-mail address: fchen@szu.edu.cn (F. Chen).

https://doi.org/10.1016/j.ins.2017.11.030
0020-0255/

Due to the population-based nature of evolutionary algorithms (EAs), they are very suitable for tackling MOPs since they can process a set of solutions in a single run. During the recent decades, a number of multi-objective EAs (MOEAs) have been designed, showing a very promising performance on tackling different MOPs. There are three well-known representatives of state-of-the-art MOEAs, *i.e.*, NSGA-II [11], SPEA2 [53], and MOEA/D [49]. Regarding NSGA-II [11], it incorporates a fast nondominated sorting approach to direct the search, while a crowding-distance metric is used to maintain the population's diversity. On SPEA2 [53], a nearest neighbor density estimation technique is proposed to maintain the population's diversity, combined with a fine-grained fitness assignment strategy that is used to guide the search. For MOEA/D [49], a MOP is decomposed into a set of SOPs and then these SOPs are solved on a cooperative manner using evolutionary search. These state-of-the-art MOEAs have inspired many enhanced variants. For example, regarding NSGA-II, a novel parent inheritance operator was embedded and several jumping gene adaptations were used in [32] to speed up convergence towards the global PF, while a reference point based approach was introduced in [12] to maintain the population's diversity when tackling many-objective optimization problems (*i.e.*, MOPs having more than three objectives); for SPEA2, a shift-based density estimation (SDE) strategy [26] was presented to enhance its performance on tackling many-objective optimization problems; with respect to MOEA/D, a dynamic resource allocation (DRA) strategy was introduced in [50] to dynamically assign the computational resources based on the difficulties of sub-problems, and an economic stable matching model (STM) was designed in [25] to guarantee the balanced match of sub-problems and solutions by mutual preferences. A detailed review of MOEAs can be found in [33]. Especially, some of MOEAs were enhanced based on the use of differential evolution (DE), since DE shows excellent search capabilities. The experiments conducted by [4] and [41] showed that DE can significantly enhance the performance of MOEAs, as the DE-based variants of three state-of-the-art MOEAs (*i.e.*, NSGA-II, SPEA2 and IBEA) significantly outperformed the original ones. In MOEA/D-DE [23] and CMODE [43], a specific DE operator was used to substitute the original evolutionary operators of MOEA/D [49] and CMPSO [48], giving rise to a better optimization performance; Moreover, in ADEMO/D [42], MOEA/D-FRRMAB [24], and MOEA/D-CDE [31], multiple DE operators were further combined to enhance their performance. These promising results have evidenced the advantages of incorporating single or multiple DE operators into a MOEA.

On the other hand, multi-objective immune algorithms (MOIAs) are designed to mimic the process of clonal selection [3,6,19,37], as inspired from the biologic immune system. The nondominated neighbor-based immune algorithm (NNIA) [19] may be the first real-coded MOIA using the clonal selection approach. Since the report of NNIA, a number of other MOIAs have been designed and enhanced under its framework [6,22,29]. Among these MOIAs, clonal selection is employed to pick out a few of less-crowded nondominated solutions, which are then proportionally cloned according to their crowding-distance values [11]. Then, the clones undergo the heuristic search operations, such as recombination and mutation. By this way, the less-crowded search area will be assigned with more clones for exploration. Note that the boundary area is considered as the sparsest area and, therefore, it will be explored by more clones. Compared to the selection operator in NSGA-II [11] and most of other MOEAs [12,33,43], clonal selection enables MOIAs to allocate more search efforts to the boundary and less-crowded areas, which helps to improve the convergence speed and tries to extend the population's diversity. However, when dealing with some complicated MOPs, MOIAs may easily fall into local optimum and suffer from premature convergence or stagnation due to the lack of population diversity [22,38], as only a few of nondominated solutions are selected for cloning, especially at the early stages of the search. To overcome this limitation, some MOIAs [27,28,30,34] have been recently proposed to embed the DE operators. These embedded DE operators have been often used to replace or cooperate with the simulated binary crossover (SBX) operator [14], as the DE operators normally show a better search capability than SBX [28]. Therefore, embedding them can help to enhance the population diversity of MOIAs. However, all the MOIAs proposed in [27,28,30,34] only adopt one single DE strategy, which may not provide optimal performance when tackling different kinds of MOPs, as different DE strategies are suitable for solving certain kinds of problems with different features [10]. Moreover, a single DE strategy with fixed parameters settings only presents a monotonous search pattern, which may limit the search capability of these MOIAs. In some MOEAs [24,31,42], it was experimentally validated that multiple DE strategies seemed more advantageous when solving different kinds of MOPs. Thus, it is reasonable to expect that, the introduction of multiple DE strategies into MOIAs may also be very promising. Therefore, in this paper, an Adaptive Immune-inspired Multi-objective Algorithm, called AIMA, is proposed in this paper. Three DE strategies with different parameters settings are embedded into a state-of-the-art MOIA (*i.e.*, NNIA [19]) and an adaptive DE strategy selection approach is designed to automatically run an appropriate DE strategy at each generation based on the current evolutionary stage. These three DE strategies can provide different search properties. Thus, they can significantly enhance the search capability and population diversity of NNIA when appropriately selected using the adaptive DE strategy. When solving the well-known and frequently-used test MOPs (WFG [20] and DTLZ [13]) with various features, AIMA shows evident advantages over five state-of-the-art multi-objective optimization algorithms (*i.e.*, NSGA-II [11], SPEA2 [53], MOEA/D [49], SMS-EMOA [2], and CMPSO [48]) and their DE-based variants [23,43], and four competitive MOIAs (*i.e.*, NNIA [19], IMADE [34], DMMO [27], and HEIA [28]).

The remainder of this paper is organized as follows. Section 2 provides some basic background on multi-objective optimization, as well as a brief introduction to MOIAs, and a description of the clonal selection operator in NNIA. The details of AIMA are given in Section 3, including the complete pseudo-code of AIMA, the three adopted DE strategies, and the adaptive DE strategy selection approach. In Section 4, our proposed AIMA is compared with respect to several state-of-the-art MOEAs and MOIAs. The advantages of our proposed mechanisms and the sensitivity of our proposed approach to its parameters are also analyzed in this section. Finally, our conclusions and some possible paths of future research are given in Section 5.