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Immune Generalized Differential Evolution for dynamic multi-objective environments: An empirical study

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ABSTRACT

In this paper, an Immune Generalized Differential Evolution 3 (Immune GDE3) algorithm to solve dynamic multi-objective optimization problems (DMOPs) is empirically analyzed. Three main issues of the algorithm are explored: (1) the general performance of Immune GDE3 in comparison with other well-known algorithms, (2) its sensitivity to different change severities and frequencies, and (3) the role of its change reaction mechanism based on an immune response. For such purpose, four performance metrics, three unary and one binary, are computed in a comparison against other state-of-the-art dynamic multi-objective evolutionary algorithms (DMOEAs) when solving a novel suite of test problems. A proposal for the adaptation of a binary metric, called Two-set-coverage, to evaluate the performance of DMOEAs is also presented in this paper. The statistically validated results indicate that Immune GDE3 is robust to change frequency and severity variations and can track the environmental change finding a good distribution of solutions. Finally, Immune GDE3 has a very competitive performance solving different types of DMOPs and this good performance is mainly attributed to its change reaction mechanism based on an immune response. Numerical results support such findings, showing that Immune GDE3 obtains good results in all performance metrics, especially in the distribution metrics: Spacing(S) and Two-set-coverage(C-metric).

1. Introduction

In the field of optimization, real-world problems have a considerable degree of complexity, and this complexity may be based on the presence of multiple conflicting objectives to be optimized. This kind of optimization problems are known as multi-objective optimization problems (MOPs). Evolutionary algorithms (EAs) have shown be good candidates to solve MOPs in a single run compared to classical methods such as gradient descent and simulated annealing [1,2]. Therefore, in the last few years, there have been significant contributions on multi-objective evolutionary algorithms (MOEAs) design. Different MOEAs currently proposed are capable of attaining the multi-objective optimization goals with high efficacy regarding convergence and diversity of solutions [3–6].

In recent years, MOPs in dynamic environments have attracted some research efforts. Therefore, the so-called Dynamic MOPs (DMOPs) are gaining attention [7]. Optimization in a changing environment is a challenging task, especially when multiple objectives need to be optimized. The search then requires a fast convergence in the current problem conditions and also quick responses after changes [8]. In this way, it is very important to design approaches that could detect a change in the environment and then find the new Pareto optimal front as soon as possible in preparation for a new change. In addition, the study on this optimization area is still limited due to a lack of standard benchmark problems and appropriated performance metrics [9–13].

Evolutionary algorithms and Artificial Immune System (AIS) have been popular to solve dynamic single objective optimization problems [14–18]. Nevertheless, such combination has been scarcely explored when solving DMOP's [8].

Recently, a new EA based on a Differential Evolution (DE) algorithm and artificial immune system called Immune GDE3 was proposed [19]. The novelty of this algorithm with respect to other approaches is the fact that the algorithm takes advantage of DE and AIS to track the changes in the environment and responds quickly when a change is detected. In preliminary tests, Immune GDE3 showed promising results when dealing with DMOPs. However, its empirical validation was very limited because the studies carried out were only focus in the proximity of solutions. So that, just one metric (Inverted Generational Distance) was adopted to evaluate its performance [19].

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Therefore, the main contribution of this work aims to provide an in-depth analysis of Immune GDE3, where the following unexplored issues are investigated:

- The ability of the algorithm to track the changes in the Pareto front and/or Pareto set, and the distribution of non-dominated solutions.
- The effects of change frequency and change severity in its overall performance.
- The role of the immune response in the performance of Immune GDE3 when solving DMOPs.

An important issue in evolutionary multi-objective optimization is the performance comparison of different algorithms. For each one of those three issues, an experiment is designed and for the empirical validation of this work, four performance metrics are computed. These metrics are traditionally used to evaluate the performance of multi-objective optimization evolutionary algorithms (MOEAs). Three of them are unary metrics already adapted to work with DMOPs (Inverted Generational Distance (IGD), Hypervolume (HV) and Spacing (S)) [7].

However, previous studies have shown in general that unary indicators are not capable of indicating whether the quality of an approximation set is better than another, even if several sets of unary indicators are used [20]. Hence, binary quality indicators enhance the empirical evidence, on which it is possible to detect whether an algorithm performs better than another. Therefore, in conjunction with unary indicators, binary ones can be used to complement the performance evaluation of an algorithm [20]. Due to this reason, among the metrics mentioned before, to the best of the author's knowledge, a binary metric has not been yet adapted to compare DMOPs. In this paper, a binary metric called C-metric is adapted to evaluate the performance of dynamic MOEAs.

On the other hand, DE has specially attracted the interest from researches due to its excellent performance solving static optimization problems [21]. However, DE has been little applied in dynamic optimization especially in Dynamic multi-objective optimization (DMOO) [22]. Therefore, another important goal of this paper aims to analyze the behavior of DE solving dynamic multi-objective problems.

The remaining of this paper is organized as follows. In Section 2 the Problem definition and basic concepts are presented. The related work concerning DMOPs is given in Section 3. Section 4 presents a detailed description of Immune GDE3. In Section 5, the experimental design is presented. The results and discussion are presented in Section 6. Finally, Section 7 provides the concluding remarks and possible directions for future work.

2. Problem formulation

Mathematically, a DMOP can be formulated as follows: Find $\vec{x}$ which minimizes:

$$\vec{f}(\vec{x},t) = [f_1(\vec{x},t), f_2(\vec{x},t), \dots, f_k(\vec{x},t)]^T \tag{1}$$

where $\vec{x}$ is the vector of decision variables, $\vec{f}$ is the set of objective functions to be minimized with respect to the variable time t, t is the discrete time instance defined as $t = (1/n_t)\lfloor(\tau/\tau_\tau)\rfloor$, where n_t, τ_τ and τ represent the severity of change, the frequency of change, and the iteration counter, respectively. $\mathcal{F}$ represents the feasible region of the feasible space solutions that change with respect to time t.

Definition 2.1. ***Pareto Dominance:*** Let f_i be an objective function. Then, a decision vector $\vec{x} = [x_1, \dots, x_n]^T$ is said to dominate $\vec{y} = [y_1, \dots, y_n]^T$ (denoted by $\vec{x} \preceq \vec{y}$) if and only if $\vec{x}$ is at least as good as $\vec{y}$ for all the objectives, i.e. $f_i(\vec{x}) \le f_i(\vec{y}), \forall_i \in \{1, \dots, k\}$; and $\vec{x}$ is strictly better than $\vec{y}$ for at least one objective, i.e. $\exists i \in \{1, \dots, k\} : f_i(\vec{x}) < f_i(\vec{y})$.

Definition 2.2. ***Pareto Optimality:*** A vector of decision variables $\vec{x}^* \in \mathcal{F}$ is Pareto optimal at time t if it is non-dominated with respect to $\mathcal{F}$. The set of all the Pareto optimal solutions is called Pareto-Optimal Set (POS) and the set of all the Pareto vectors is the Pareto-Optimal Front (POF).

Farina et al. [23] classified the dynamic environments for DMOPs in four types:

- **Type I:** The POS changes, whereas the POF (optimal objective values) does not change.
- **Type II:** Both POS and POF change.
- **Type III:** POS does not change, whereas POF changes.
- **Type IV:** Both POS and POF remain unchanged with time but other changes in the problem definition induce dynamicity.

In this work, DMOPs with the first three types of changes indicated above without constraints were considered for the experiments. In this kind of problems, the change frequency (τ_τ) and change severity (n_t) parameters control the environmental changes. When a change occurs in the environment, the POF can change over time in different ways [23]:

- The shape of the POF can change over time from convex to nonconvex and/or viceversa. The POF changes from continuous front to disconnected front. This kind of changes is common with either type II or type III DMOPs.
- The shape of the POF remains the same, but its location in the objective space changes over time. This kind of change occurs with DMOPs of type I.
- The density of the solutions in the POF changes over time. This kind of change can occur with all types of DMOPs.

3. Related work

Different approaches have been proposed to solve DMOPs. They are focused on tracking the moving optima when a change is detected in the problem landscape. Some of the most traditional algorithms proposed in the specialized literature to deal with DMOPs are briefly discussed in this section.

One of the first algorithms proposed to solve DMOPs namely HMCEDA (Hybridized Minimal Cost Evolutionary Deterministic Algorithm) was introduced by Farina et al. [23]. This method can obtain some Pareto-optimal solutions with uniform distribution for a given problem, but time consumptions are expensive. In such work, the authors proposed five dynamic multi-objective test problems. Based on the well-known multi-objective optimization algorithm NSGA-II, Deb et al. [24] extended it to handle a dynamic multi-objective problem (dynamic hydrothermal power scheduling problem). Two dynamic optimization techniques called DNSGAII-A and DNSGAII-B were proposed. Their main difference is only the way of generating the initial population after a change. In the first case, the population is reinitialized while in the second the population is mutated depending on the type of change in the environment. The two versions were tested on a two-objective dynamic problem and applied to the problem of dynamic hydrothermal power scheduling. More recently in [25], a dynamic version of NSGA-II was proposed with an adaptive hybrid population management strategy to detect the change severity and adjust the number of random solutions to be used. Zeng et al. [26], proposed a dynamic orthogonal multiobjective evolutionary algorithm called DOMOEA. This approach, selects randomly between a linear crossover operator and an orthogonal crossover operator. The linear operator is employed as a diversity maintenance scheme and the orthogonal operator is used to enhance the fitness of the population while the problem remains stabilized between changes. The weakness of this algorithm is that it is used mainly when