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C-Multi: A competent multi-swarm approach for many-objective problems

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ABSTRACT

One of the major research topics in the evolutionary multi-objective community is handling a large number of objectives also known as many-objective optimization problems (MaOPs). Most existing methodologies have demonstrated success for problems with two and three objectives but face significant challenges in many-objective optimization. To tackle these challenges, a hybrid multi-swarm algorithm called C-Multi was proposed in a previous work. The project of C-Multi is based on two phases; the first uses a unique particle swarm optimization (PSO) algorithm to discover different regions of the Pareto front. The second phase uses multiple swarms to specialize on a dedicate part. On each sub-swarm, an estimation of distribution algorithm (EDA) is used to focus on convergence to its allocated region. In this study, the influence of two critical components of C-Multi, the archiving method and the number of swarms, is investigated by empirical analysis. As a result of this investigation, an improved variant of C-Multi is obtained, and its performance is compared to I-Multi, a multi-swarm algorithm that has a similar approach but does not use EDAs. Empirical results fully demonstrate the superiority of our proposed method on almost all considered test instances.

1. Introduction

Recently, as many real-world applications involve four or more objectives [1], the evolutionary multi-objective optimization (EMO) community has focused its attention to handle large number of objectives (Many-objective optimization problems, MaOPs). Since, several studies pointed that Pareto based algorithms scale poorly in MaOPs [2–4] because of the increase in the number of non-dominated solutions which deteriorates the selection pressure compromising the convergence to the Pareto front and diversity of the solutions.

In a previous work [5] we presented a hybrid algorithm called C-Multi to deal with this challenge. The project of C-Multi is based on two phases: the first uses a unique particle swarm optimization algorithm (PSO) [6] to discover the different regions of the Pareto front. The second phase uses multiple swarms to specialize on a dedicate part. On each swarm, an estimation of distribution algorithm (EDA) [7] is used to focus on convergence to its allocated region. The study featured a comparative study involving the C-Multi and the I-Multi algorithms using the DTLZ [8] family of benchmark problems. I-Multi is a multi-swarm algorithm that has a similar project to C-Multi but does not incorporate probabilistic modeling to the search as C-Multi does. The result of the comparison was that C-Multi achieved good results in some problems, but performed poorly in general.

Here, in this study, our goal is to investigate the following hypothesis: H_1 the performance of C-Multi can be further improved by an appropriate adjustment of two critical components of the algorithm; the type of archiving method, and the number of swarms. We initially hypothesized that finding a robust setting for these two components, together with the use of EDAs, could enhance C-Multi and help it to overcome I-Multi in the general case. To investigate this hypothesis, firstly we conducted two studies on the impact of C-Multi components. One of them evaluated the effect of the archiver used in the multi-swarm phase of the algorithm. The other assessed the effect of the number of sub-swarms. Next, we conducted extensive experimentation to compare the performances of C-Multi, enhanced with our findings from the previous studies, and I-Multi. Moreover, we compared both algorithms to a state-of-the-art algorithm called MOEA/D-DRA [9] in order to assess the effectiveness of the new algorithm. The obtained results indicate that C-Multi can be a competitive

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algorithm and the use of EDAs is a promising area in many-objective optimization.

The remaining of this paper is organized as follows: the next section presents related works. Some background concepts are described in Section 3. Section 4 presents the C-Multi algorithm. Experimental studies to investigate the influence of components of C-Multi, as well as an empirical study comparing it to I-Multi and MOEA/D-DRA are reported in Section 5. And finally, Section 6 presents the conclusions.

2. Related works

Multi-Objective Evolutionary Algorithms (MOEAs) modify EAs by incorporating a selection mechanism that is based on Pareto optimality and by adopting a diversity preservation mechanism that avoids the convergence to a single solution [10]. Although most of the studies on MOPs have focused on problems that have a small number of objectives, practical optimization problems involve a large number of criteria [11]. Therefore, research efforts have been oriented toward investigating the scalability of these algorithms with respect to the number of objectives [12]. Several studies have shown that MOEAs scale poorly in MaOPs [12,13]. The main reason for this scaling property is that the number of non-dominated solutions increases exponentially with the number of objectives. The following consequences occur: First, the search ability deteriorates because it is not possible to impose preferences for selection purposes, since most elite preserving mechanisms of MOEAs employ Pareto dominance as a major selection criterion. Second, the number of solutions that are required for approximating the entire Pareto front increases, therefore, in a high-dimensional objective space a limited number of solutions are likely to be far away from each other.

Among the studies presented in the literature, several papers address the issues of Many-Objective Optimization and deserve to be highlighted. In [14], an extension of the NSGA-II algorithm applied to MaOPs is presented. The new algorithm, known as NSGA-III, uses a set of reference points that are aimed at guiding the search toward the Pareto front without losing diversity. These points help the convergence and the diversity of the algorithm. Basically, the proposed algorithm builds niches for each reference point. Thus, the specialization of the algorithm enables convergence, and the different niches enable diversification. With these goals, the authors proposed a new density estimator that calculates the concentration of solutions around the reference points. Solutions that are close to less crowded reference points obtain an advantage in the selection process, similar to the crowding distance in NSGA-II. The NSGA-III was compared to MOEA/D [15], a decomposition based algorithm, and the best results were presented for different many-objective scenarios. More recently, in [16] a unified framework exploits dominance and decomposition based approaches from NSGAII and MOEAD/D to tackle MaOPs. The results of this unified framework have demonstrated its capability to find a well converged and well distributed approximation of the Pareto front.

In spite of the existence of different studies that address MaOPs, until very recently, most of these research studies focused on a small group of algorithms, often the NSGA-II or MOEA/D. In our project, the behavior of the PSO in MaOPs is investigated, since this approach has shown to be very efficient both in single-objective and in multi-objective optimization problems from different domains [17,18]. Its idea of moving across the search space towards the best solutions found so far while keeping a diverse population, points to the convenience of applying this method to MaOPs, where convergence and diversity are needed for a good coverage of the Pareto front. Therefore, PSO is a suitable algorithm for continuous many-objective optimization, but it is still under-explored in the literature.

In this direction, it can be mentioned the work presented in [4] that investigates several archiving methods, among them the Ideal and Multi-level Grid Archiving (MGA) [19]. The Ideal archiving method increases the convergence of the non-dominated solutions towards the Pareto-optimal front. On the other hand, the MGA approach obtains good diversity of solutions. The conclusion of the work highlights the main challenge of MaOPs: convergence to the true Pareto front and diversity of the obtained solutions covering the entire Pareto front. Recently, to overcome this limitation, researches proposed the use of multiple swarms. I-Multi algorithm [3] combines Ideal and MGA archivers in a multi-swarm search. This algorithm uses these two archiving methods at different phases of the process: first, the MGA is used in a single swarm, and after the obtained front is split and different swarms are executed in parallel using Ideal archiver. I-Multi algorithm presents good results in terms of convergence to the Pareto front and diversity of the obtained solutions on a set of MaOP benchmark problems.

These researches motivated our previous work [5] where the main goal was to explore other strategies of combination of these good elements in the design of algorithms for MaOPs. In [5], a possible alternative for the second phase of the I-Multi was investigated. The algorithm C-Multi was proposed whose main feature was to use an EDA [7]. EDAs have the capacity of achieving good convergence by generating solutions learned from the shape of the Pareto front. This work is an extension of the investigation presented in [5]. Our goal is to investigate if the performance of C-Multi can be enhanced by a more appropriate choice of its components. To evaluate the behavior of the algorithm, we compare to I-Multi, an algorithm that is similar to C-Multi but does not incorporate EDAs as part of the optimization process and to MOEA/D-DRA, a highly efficient method recently introduced in [9] as an improvement to MOEA/D [15].

3. Preliminaries

In this section, we first introduce some basic knowledge about many-objective optimization. Then, we briefly introduce the general mechanism of multi-objective particle swarm optimization (MOPSO) and I-Multi that are related to our work. Finally, we review basic knowledge about EDAs.

3.1. Many-objective optimization

Multi-objective optimization problems (MOPs) require the simultaneous optimization (maximization or minimization) of two or more objective functions. These objectives are usually in conflict, so these problems do not have only one optimal solution (as in single objective optimization problems), but a set of them. This set of solutions is usually found using Pareto optimality theory.

A general unconstrained MOP can be defined as optimizing $\vec{f}(\vec{x}) = (f_1(\vec{x}), \ldots, f_m(\vec{x}))$, where $\vec{x} \in \Omega$ is an n-dimensional decision variable vector $\vec{x} = (x_1, \ldots, x_n)$ from a universe Ω, and m is the number of objective functions.

An objective vector $\vec{f}(\vec{x})$ dominates a vector $\vec{f}(\vec{y})$, denoted by $\vec{f}(\vec{x}) \preceq \vec{f}(\vec{y})$ (in case of minimization) if and only if $\vec{f}(\vec{x})$ is partially less than $\vec{f}(\vec{y})$ i.e., $\forall i \in \{1, \ldots, m\}$, $f_i(\vec{x}) \le f_i(\vec{y}) \wedge \exists i \in \{1, \ldots, m\} : f_i(\vec{x}) < f_i(\vec{y})$.

A vector $\vec{f}(\vec{x})$ is non-dominated if there is no $\vec{f}(\vec{y})$ that dominates $\vec{f}(\vec{x})$. If $\vec{f}(\vec{x})$ is non-dominated, $\vec{x}$ is Pareto optimal. The set of Pareto optimal solutions is called Pareto optimal set, and