Balancing Exploration and Exploitation in Multiobjective Evolutionary Optimization

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ABSTRACT

Balancing exploration and exploitation is fundamental to the performance of an evolutionary algorithm. In this paper, we propose a survival analysis method to address this issue. Results of the analysis is used to adaptively choose appropriate new solution creation operators which prefer either exploration or exploitation. In the developed algorithm, a differential evolution recombination operator is used for the exploration purpose, while a new clustering-based operator is proposed for exploitation. Empirical comparison with four well-known multi-objective evolutionary algorithms on test instances with complex Pareto sets and Pareto fronts indicates the effectiveness and outperformance of the developed algorithms on these test instances in terms of commonly-used metrics.

CCS CONCEPTS

• **Theory of computation → Bio-inspired optimization**;

KEYWORDS

Multiobjective optimization, exploration and exploitation

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1 INTRODUCTION

The main operations of an evolutionary algorithm (EA) include recombination and environmental selection, where recombination is responsible to create new solution and environmental selection is to determine which new solutions survive. The selection operation drives the evolutionary search towards optimality. It works together with recombination which determines the search effectiveness and efficiency. Keeping a good ratio between exploration and exploitation is fundamental to the success of EA (and MOEA) [4]. It is still an open question on how to measure the balance [2].

In EAs for single-objective optimization, usually the population diversity in the *search space* is used to measure the balance since exploration is only possible if the population is diverse. And the diversity is expected to decrease in the phase of exploitation. On the contrary, MOEAs need to maintain the diversities of the solutions both in the *objective space* and *search space*. Moreover, different to single-objective EAs, the population diversity should not be decreased along the search to make sure the diversity of the final solutions in the objective space.

In existing MOEAs, it is assumed that selection in the objective space will maintain the diversity *per se* in the search space. No explicit mechanism is embedded in existing MOEAs to control the balance of exploration and exploitation. Practically, it is found that the collaboration of multiple recombination operators can adapt to the the shape and local properties of the fitness landscape, which helps to balance the exploration and exploitation.

In view of this, we thus focus on hybridizing recombination operators with relatively explicit preferences on exploration/exploitation. Notice that the DE/rand/1/bin mutation prefers exploration if the reference individuals are far from each other [3] while a recombination operator based on Gaussian sampling strongly prefer exploitation. Further, the pattern observed from the average survival time of non-dominated solutions during the search is formulated and applied to control the contribution of the recombination operators on generating new solutions.

2 THE ALGORITHM

We consider the following box-constrained continuous MOPs:

$$\begin{array}{ll} \min & \mathbf{F}(\mathbf{x}) = (f_1(\mathbf{x}), \cdots, f_m(\mathbf{x}))^\intercal \\ \text{s.t.} & \mathbf{x} = (x_1, \cdots, x_n)^\intercal \in \Omega \end{array} \tag{1}$$

The developed algorithm is called Exploration/Exploitation Multiobjective Evolutionary Algorithm (EMEA). It maintains a population

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of solutions $\mathcal{P}$ and an external archive $\mathcal{A}$. The algorithmic parameters include the population size N, the number of partitions K, and two initial control parameters $\alpha_0, \beta_0 \in [0, 1]$.

In EMEA, at each generation, first whether K-means should be applied or not is decided. If α is bigger than α_0, K-means is employed to partition $\mathcal{P}$ to $\{C_k, 1 \leq k \leq K\}$; otherwise, most recent clustering results is reused. At each generation t, around each solution $\mathbf{x}_t \in C_k$, with probability β (it is initialized to be β_0), a trial solution is sampled from $\mathcal{N}(\mu_k, \Sigma_k)$; otherwise, two random solutions from outside C_k are chosen for DE/rnd/1. The external archive is updated incrementally whenever a new trial solution is generated by environmental selection. The hypervolume metric-based environmental selection proposed in SMS-EMOA [1] is adopted to choose promising solutions for the next population. α and β are then computed according to previous search history. EMEA iterates for T generations and returns the external archive.

The value of α reflects the stagnation of the population, while β determines the exploration/exploitation tradeoff. α is computed as the ratio of the changed solutions to the population size between adjacent generations. To compute β, a survival analysis is used based on the simple fact: high-quality solution will survive longer than low-quality solutions. First, at each generation, the survival time of each solution at its position in the population is computed. Then the average survival time of each solution along the previous H generations, i.e. β, is computed.

3 EXPERIMENTAL STUDY

Three well-known MOEAs including RM-MEDA [8], MOEA/D-DE [5] and T-MOEAD [6] are compared with EMEA on GLT [7]. The inverted generational distance (IGD) is used to compare the performance of MOEAs. The statistical results of IGD of the final approximated Pareto fonts on the test suites yielded by the compared algorithms are presented in Table 1. From the table, we may conclude that EMEA outperforms the compared algorithms.

Table 1: Statistics of the IGD metric values obtained by RM-MEDA, MOEA/D-DE, TMOEA/D, and EMEA on GLT.

Instance	RM-MEDA	MOEA/D-DE	TMOEA/D	EMEA
GLT1	1.686e-02$^{\dagger}_{1.65e-02}$	7.167e-03$^{\dagger}_{1.58e-03}$	4.493e-03$^{\dagger}_{5.57e-04}$	1.927e-03$_{1.77e-04}$
GLT2	3.521e-02$^{\dagger}_{9.73e-03}$	3.754e-01$^{\dagger}_{8.17e-02}$	3.558e-02$^{\approx}_{3.78e-03}$	3.497e-02$_{6.97e-04}$
GLT3	2.358e-02$^{\dagger}_{9.67e-03}$	3.951e-02$^{\dagger}_{1.19e-02}$	2.876e-02$^{\dagger}_{5.65e-02}$	6.484e-03$_{3.14e-03}$
GLT4	5.166e-02$^{\dagger}_{5.13e-02}$	1.924e-02$^{\dagger}_{1.91e-03}$	1.854e-02$^{\dagger}_{4.08e-02}$	9.903e-03$_{2.34e-02}$
GLT5	5.135e-02$^{\dagger}_{1.93e-03}$	8.096e-02$^{\dagger}_{2.46e-03}$	4.450e-02$^{\dagger}_{1.04e-03}$	2.889e-02$_{3.27e-04}$
GLT6	3.786e-02$^{\dagger}_{1.77e-03}$	5.570e-02$^{\dagger}_{2.29e-02}$	4.140e-02$^{\dagger}_{3.43e-02}$	2.176e-02$_{5.89e-04}$

To show the superiority of EMEA, Fig. 1 shows the obtained PFs with median IGD by EMEA and TMOEA/D. It is apparent to see that EMEA is much better than T/MOEAD on visual comparison of AFs. The AFs found by T/MOEAD can not cover the whole PFs for GLT5-GLT6, e.g. T/MOEAD fail to converge to the PF of GLT3 and GLT4. By contrast, representative AFs achieved by EMEA are able to approximate to PFs and uniformly spread on the whole PFs.

4 CONCLUSIONS

An adaptive MOEA combining a sampling strategy and DE was proposed in this paper. The contributions of these recombination operators are controlled by a newly proposed survival analysis along the evolutionary search. A reusing scheme is employed in EMEA to reduce the computational cost on clustering. Comparison experiments with three well-known MOEAs were conducted MOPs with complex PSs and PFs. Experimental results suggested that EMEA significantly outperforms the compared algorithms in terms of convergence and diversity measured by IGD and HV.

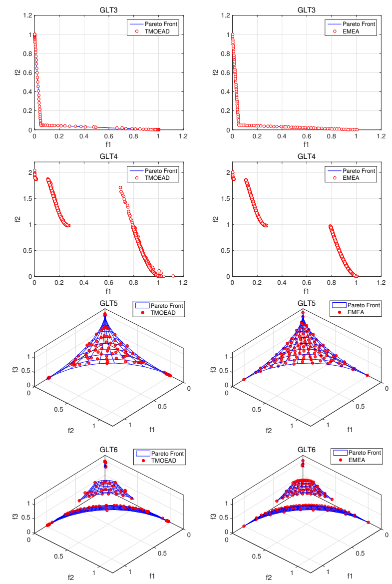

Figure 1: The final solutions obtained by TMOEA/D, and EMEA on GLT3-GLT6 with the median IGD metric values.

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REFERENCES

[1] Nicola Beume, Boris Naujoks, and Michael Emmerich. 2007. SMS-EMOA: Multiobjective selection based on dominated hypervolume. *European Journal of Operational Research* 181, 3 (2007), 1653–1669.
[2] H.-G. Beyer and K. Deb. 2001. On self-adaptive features in real-parameter evolutionary algorithms. *IEEE Transactions on Evolutionary Computation* 5, 3 (2001), 250–270.
[3] S. Das and P.N. Suganthan. 2011. Differential Evolution: A Survey of the State-of-the-Art. *IEEE Transactions on Evolutionary Computation* 15, 1 (2011), 4–31.
[4] Francisco Herrera and Manuel Lozano. 1996. Adaptation of Genetic Algorithm Parameters Based on Fuzzy Logic Controllers. In *Genetic Algorithms and Soft Computing*. Physica-Verlag, 95–125.
[5] Hui Li and Qingfu Zhang. 2009. Multiobjective Optimization Problems With Complicated Pareto Sets, MOEA/D and NSGA-II. *IEEE Transactions on Evolutionary Computation* 13, 2 (2009), 284–302.
[6] Hai Lin Liu, Fang Qing Gu, and Yiu Ming Cheung. 2010. T-MOEA/D: MOEA/D with Objective Transform in Multi-objective Problems. In *Information Science and Management Engineering*. 282–285.
[7] Hu Zhang, Aimin Zhou, Shenmin Song, Qingfu Zhang, Xiao-Zhi Gao, and Jun Zhang. 2016. A self-organizing multiobjective evolutionary algorithm. *IEEE Transactions on Evolutionary Computation* (2016).
[8] Qingfu Zhang, Aimin Zhou, and Yaochu Jin. 2008. RM-MEDA: A Regularity Model Based Multiobjective Estimation of Distribution Algorithm. *IEEE Transactions on Evolutionary Computation* 12, 1 (2008), 41–63.