Supplementary Materials of ”A Relation-and-Regression-assisted Evolutionary Algorithm for Expensive Constrained Multi-objective Optimization”

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I. General Framework of RCMOEA

RCMOEA adopts the two-stage strategy for handling expensive CMOPs, for it accelerates the convergence and promotes the diversity of the population with only few generations [1] [2]. As illustrated in Fig. 1, in the beginning, RCMOEA initializes the solution population P and an empty archive A that store solutions evaluated by expensive objectives and constraints. After evaluating solutions in P, a CMOP without considering constraints is optimized in the first stage, and the original CMOP is optimized in the second stage. The switching strategy from one stage to the other in RCMOEA is identical with the one in MGSAEA, where the switch is triggered by the maximum change rate γ of ideal points during the past Δt generations. It is calculated in (1):

$$\gamma = \max_{i=1,2,\ldots,m} \left\{ \frac{|f_i^t - f_i^{t-\Delta t}|}{\max\{|f_i^{t-\Delta t}|, \delta\}} \right\} \tag{1}$$

where f_i^t is the i-th objective value of ideal points in P at the t-th generation, and δ is a constant to ensure that the denominator is not zero. The values of Δ and δ are identical to ones in MGSAEA, which are 20 and 1e-6, respectively. RCMOEA switches to the second stage if γ is below the threshold λ. The two-stage surrogate-assisted evolutionary search iterates for many generations until the termination condition is met. The optimal solutions in A are final solutions of RCMOEA.

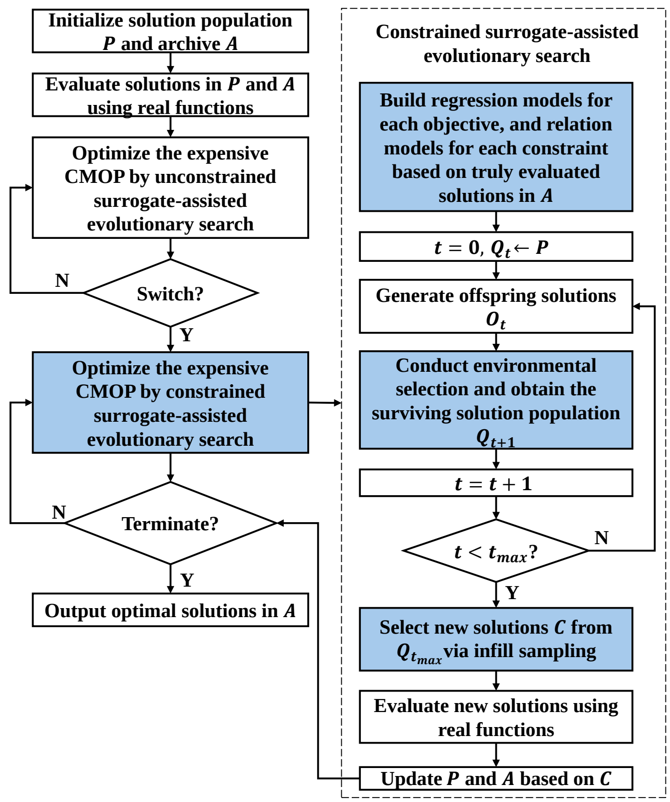
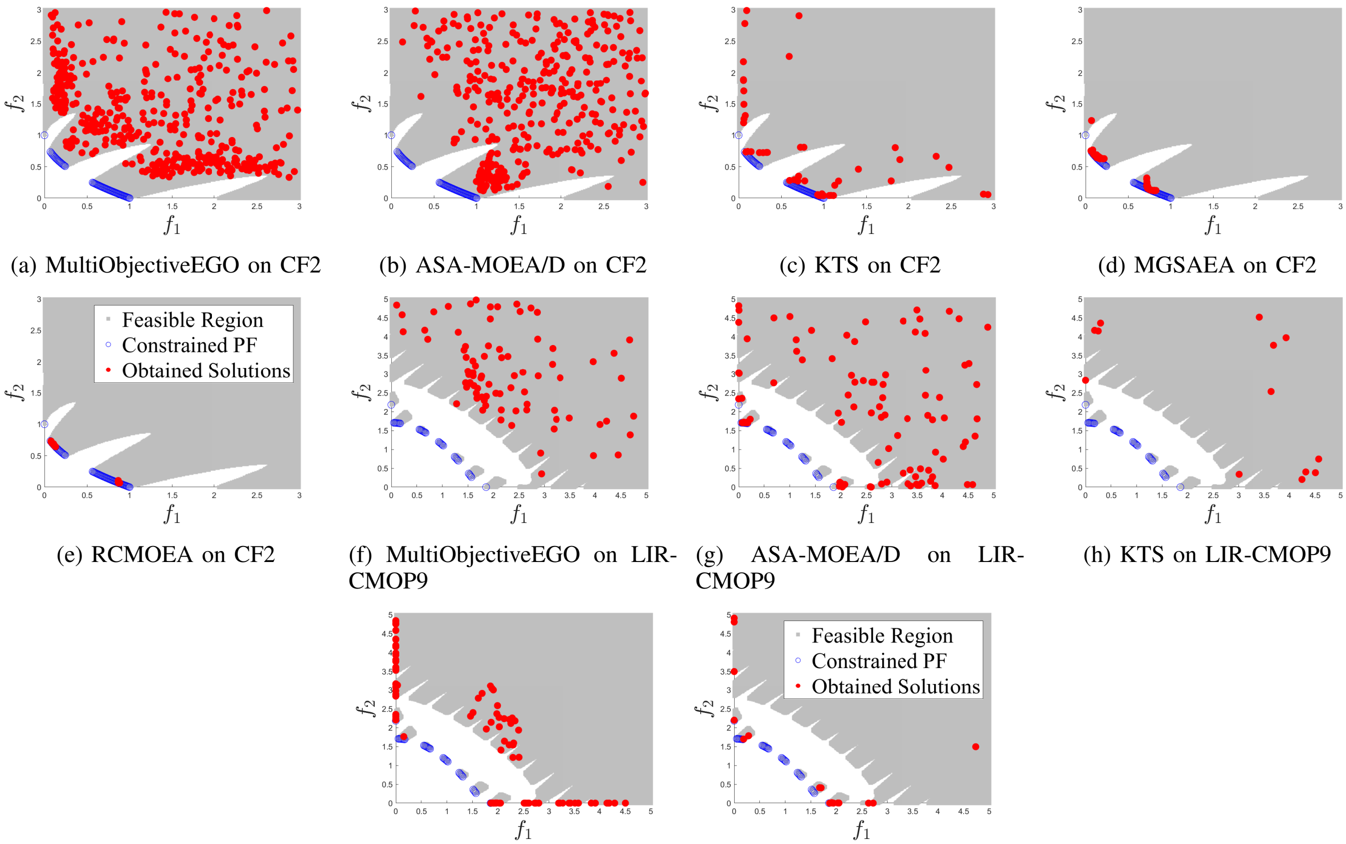


Fig. 1: A general overview of the proposed RCMOEA framework. The blue shaded boxes indicate the steps where this work makes contributions.

II. Performance Comparison among Algorithms

To gain the insight of the optimization results, Fig. 2 visualizes the populations with median IGD obtained by the five compared algorithms on CF2 and LIR-CMOP9 test problem, respectively. In CF2, the CPF shares disconnected segments with UPF. It can be seen that MultiObjectiveEGO and ASA-MOEA/D cannot approach the CPF. Though KTS and MGSAEA find subsets of CPF, RCMOEA is able to locate the CPF precisely. That's because RCMOEA prefers solutions with more HVC, which are more likely to drive the solution population towards UPF.

In LIR-CMOP9, the CPF locates in the disjoint and tiny feasible regions obstructed by large infeasible barrier. Hence, in order to cover CPF, both convergence and diversity should be emphasized during the search. According to Fig. 2, MultiObjectiveEGO and KTS cannot pass through infeasible regions. ASA-MOEA/D and MGSAEA only capture few subsets of CPF. By contrast, MGSAEA is able to obtain more solutions on CPF. On one hand, RCMOEA adopts the two-stage evolutionary search. Since the optimization does not consider constraints in the first stage, the solution population can cross infeasible regions to approach UPF. On the other hand, the proposed RCPD in selecting candidate solutions maintains the diversity of solution population. Therefore, RCMOEA is able to cover the disconnected CPF.



(a) MultiObjectiveEGO on CF2 (b) ASA-MOEA/D on CF2 (c) KTS on CF2 (d) MGSAEA on CF2

(e) RCMOEA on CF2 (f) MultiObjectiveEGO on LIR-CMOP9 (g) ASA-MOEA/D on LIR-CMOP9 (h) KTS on LIR-CMOP9

(i) MGSAEA on LIR-CMOP9 (j) RCMOEA on LIR-CMOP9

Fig. 2: Populations with the median IGD obtained by MultiObjectiveEGO, ASA-MOEA/D, KTS, MGSAEA and RCMOEA on CF2 and LIR-CMOP9 test problem.

References

[1] Y. Zhang, H. Jiang, Y. Tian, H. Ma, and X. Zhang, "Multigranularity surrogate modeling for evolutionary multiobjective optimization with expensive constraints," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 35, no. 3, pp. 2956–2968, 2024.

[2] Z. Song, H. Wang, B. Xue, M. Zhang, and Y. Jin, "Balancing objective optimization and constraint satisfaction in expensive constrained evolutionary multi-objective optimization," *IEEE Transactions on Evolutionary Computation*, 2023.