

# CORAL-DMOEA: Correlation Alignment-Based Information Transfer for Dynamic Multi-Objective Optimization (Student Abstract)

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## Abstract

One essential characteristic of dynamic multi-objective optimization problems is that Pareto-Optimal Front/Set (POF/POS) varies over time. Tracking the time-dependent POF/POS is a challenging problem. Since continuous environments are usually highly correlated, past information is critical for the next optimization process. In this paper, we integrate CORAL methodology into a dynamic multi-objective evolutionary algorithm, named CORAL-DMOEA. This approach employs CORAL to construct a transfer model which transfer past well-performed solutions to form an initial population for the next optimization process. Experimental results demonstrate that CORAL-DMOEA can effectively improve the quality of solutions and accelerate the evolution process.

## Introduction

Dynamic Multi-objective Optimization Problems (DMOPs) are more challenging than static ones. A converged population is hard to adapt to a changing environment in time as it loses the exploration ability (Qian et al. 2017). Restarting optimization may be straightforward but ineffective. Usually, a new environment is strongly relevant to the previous one, so reusing experience has enormous potential to accelerate the next optimization process.

In recent years, transfer learning method has gradually aroused considerable interest. For instance, (Jiang et al. 2018) proposed Tr-DMOEA, which combines TCA with DMOEA. (Liu et al. 2019) proposed a Neural Network-based Information Transfer method (NNIT) which learns how the environment changes. However, all these methods need to fine-tune the hyperparameters during the optimization process.

In this paper, we propose an algorithmic framework, which integrates a non-parametric domain adaptation method, CORrelation ALignment, into DMOEA, named CORAL-DMOEA.

## Proposed Algorithm

CORAL-DMOEA is described in Algorithm 1. Once the environment changes, CORAL based Initial Population Gener-

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## Algorithm 1 CORAL-DMOEA

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**Input:** Dynamic Optimization Function  $F(\cdot)$ ; Dynamic Multi-objective Evolutionary Algorithm (DMOEA);

**Output:** The POFs of the  $F(\cdot)$ ;

- 1: Obtain  $POF_0$  by employing a **DMOEA** to solve  $F_0(\cdot)$ ;
- 2: **for**  $t = 1$  to *iteration\_count* **do**
- 3:   **if** environment changes **then**
- 4:     Next-Pop = **CORAL-IPG**( $F_t(\cdot)$ ,  $POF_{t-1}$ );
- 5:      $POF_t =$  **DMOEA** (Next-Pop);
- 6:   **else**
- 7:     Offspring reproduction;
- 8:   **end if**
- 9: **end for**
- 10: **return**  $POF_s$ ;

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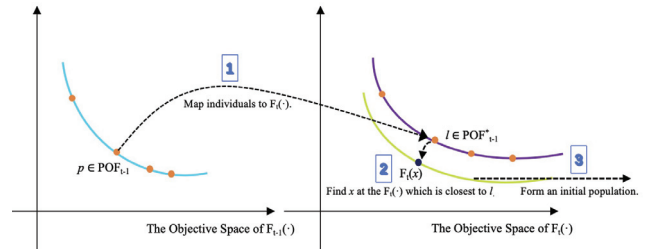


Figure 1: The key steps of CORAL-IPG.

ator (CORAL-IPG) establishes an initial population for the next evolutionary process. Figure 1 illustrates the key steps of CORAL-IPG. Step 1 maps individuals in the obtained  $POF_{t-1}$  to the objective space of  $F_t(\cdot)$ , named  $POF_{t-1}^*$ . Afterwards, for each  $l \in POF_{t-1}^*$ , Step 2 finds the corresponding  $x \in F_t(\cdot)$  which is the closest to  $l$ . Finally, Step 3 outputs the set of corresponding individuals as the initial population. This figure represents the operation process from Line 3 to Line 8 of Algorithm 2.

CORAL uses covariance to evaluate the distances between different environments and aligns the data distribution in the past with the one in the current via minimizing the covariances. In the new objective space, the data feature of the past and new environments obey similar distributions as far

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**Algorithm 2** CORAL-IPG

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**Input:** Dynamic Optimization Function  $F_t(\cdot)$ ; Actual POB obtained by the algorithm at time  $t - 1$ ,  $POF_{t-1}$ ;

**Output:** Initial Population at time  $t$ , **Next-Pop**;

- 1: Generate solutions  $X_s$  and  $X_t$  randomly;
  - 2: For optimization functions  $F_{t-1}(\cdot)$  and  $F_t(\cdot)$ , calculate the objective values  $F_{t-1}(X_s)$  and  $F_t(X_t)$ ;
  - 3:  $POF_{t-1}^* = \mathbf{CORAL}(F_{t-1}(X_s), F_t(X_t), POF_{t-1})$ ;
  - 4: **for** each  $l \in POF_{t-1}^*$  **do**
  - 5:      $x \leftarrow \arg \min_x \|F_t(x) - l\|$ ;
  - 6:     **Next-Pop** = **Next-Pop**  $\cup \{x\}$ ;
  - 7: **end for**
  - 8: **return** **Next-Pop**;
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as possible.

Furthermore, the output of CORAL-IPG is an initial population. Thus we can combine any population-based DMOEA with CORAL-IPG to get a CORAL based dynamic evolutionary algorithm.

### Empirical Study

We employ the IEEE CEC 2015 benchmark problem (Helbig and Engelbrecht 2015) to investigate the performances under different frequency changes. The frequency of change  $\tau_t$  is set to 25, 50, 100, and 200 respectively, and the corresponding iteration count  $\tau$  is 500, 1000, 2000, and 4000. Each function changes 20 times during a run, and each algorithm runs 30 times on each test function. Before the first change occurs, each algorithm runs 300 generations, and the population size is 300.

MIGD and MHV are comprehensive performance metrics which provide an overall assessment of the convergence and diversity of algorithms. Table 1 illustrates the ratio of change (ROC) between DMOEAs and CORAL-DMOEAs on MIGD and MHV metrics. The best metric values are highlighted in the boldface.

We analyze the experimental results as a whole and draw the following conclusions. The overall effective rate of the CORAL-DMOEAs in MIGD metric is 87.50% (i.e., 21 cases perform well in 24 test functions). The results in FDA4, DMOP2\_dec, and HE2 perform excellently. They belong to different DMOP types (Helbig and Engelbrecht 2015), which means that the proposed algorithm works on all types of DMOPs. The overall effective rate of the CORAL-DMOEAs in MHV metric is 91.67%. However, the results in FDA5\_iso and DMOP2\_iso do not behave well, which means that the proposed algorithm may not be suitable for the isolated functions. Thus, CORAL can significantly improve the performances of the DMOEAs.

### Conclusion and Future Work

In this paper, we propose an algorithmic framework CORAL-DMOEA. The combination of CORAL and DMOEAs accelerates the re-convergence of the population via reusing experience. Besides, the advantages of DMOEAs for solving DMOPs are preserved. The experimental results prove the superiority of CORAL-DMOEA.

ROC (%)	CORAL-MOEA/D	CORAL-NSGA-II
FDA4	<b>80.10</b>	<b>79.56</b>
FDA5	<b>20.53</b>	<b>15.01</b>
FDA5_iso	<b>16.01</b>	<b>97.02</b>
FDA5_dec	<b>50.92</b>	<b>50.28</b>
DIMP2	<b>66.85</b>	<b>24.45</b>
DMOP2	<b>1.13</b>	<b>13.09</b>
DMOP2_iso	<b>1.59</b>	-9.06
DMOP2_dec	<b>89.82</b>	<b>81.86</b>
DMOP3	-0.79	<b>73.29</b>
HE2	<b>95.03</b>	<b>86.06</b>
HE7	<b>52.85</b>	<b>60.38</b>
HE9	<b>13.33</b>	-6.86

(a) ROC values of CORAL-DMOEAs on MIGD

ROC (%)	CORAL-MOEA/D	CORAL-NSGA-II
FDA4	<b>104.56</b>	<b>2327.16</b>
FDA5	<b>2.86</b>	<b>70.24</b>
FDA5_iso	<b>3.04</b>	-14.39
FDA5_dec	<b>325.32</b>	<b>4693.92</b>
DIMP2	<b>2435.12</b>	<b>2019.04</b>
DMOP2	<b>212.25</b>	<b>122.04</b>
DMOP2_iso	<b>0.43</b>	<b>0.83</b>
DMOP2_dec	<b>1065.38</b>	<b>215.40</b>
DMOP3	<b>96.98</b>	<b>71.53</b>
HE2	<b>554.50</b>	<b>156.07</b>
HE7	<b>30.53</b>	<b>26.93</b>
HE9	<b>25.82</b>	-5.80

(b) ROC values of CORAL-DMOEAs on MHV

Table 1: The comparison between DMOEAs and CORAL-DMOEAs (ROC means the ratio of change)

In future, we will employ the CORAL-DMOEA in practical application.

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