MOEA-AP: A Multiobjective Evolutionary Algorithm with Adaptive Simulated Binary Crossover and Pareto Front Modeling

Jiangtao Shen, Junchang Liu, Huachao Dong, Xinjing Wang, and Peng Wang
School of Marine Science and Technology
Northwestern Polytechnical University
Xi'an, 710072, China
J. Shen: shen_jiang_tao@163.com, J. Liu: liujunchang_nwpu@mail.nwpu.edu.cn,
H. Dong: hdong@nwpu.edu.cn, X. Wang: wangxinjing0213@nwpu.edu.cn, P. Wang: wangpeng305@nwpu.edu.cn

***Abstract*—A multiobjective evolutionary algorithm with adaptive simulated binary crossover and Pareto front modeling, termed MOEA-AP, is proposed in this report to participate in the Multiobjective Neural Architecture Search Challenge for Real-Time Semantic Segmentation in IEEE WCCI 2024. According to the experimental results, the proposed method shows significant superiority when compared with NSGA-II on the CitySegMOP test suite.**

I. The Proposed Method

Offspring generation and environmental selection are two critical parts for the performance of evolutionary multiobjective algorithms (MOEAs). Therefore, we develop the MOEA-AP considering the above perspectives for better performance on multiobjective Neural Architecture Search (NAS) problems [1]. First, the adaptive rotation-based simulated binary crossover (ARSBX) [2] is applied to generate offspring. Second, the selection strategy based on Pareto front modeling is used for environmental selection in the proposed MOEA-AP, which is the same with that of AGE-MOEA-II [3].

The pseudocode of the proposed MOEA-AP is presented in Algorithm 1, which could be divided into the following seven steps:

1) Initialization (line 1): A population with N individuals is generated randomly in the decision space;
2) Preparation (lines 2-3): Calculate the nondominated level/front number FN and the survival score S of individuals in P; Set $NFE = N$;
3) Parents Selection (line 5): Select N parents P' via binary tournament selection according to FN and S;
4) Offspring Generation (line 6): Use ARSBX to generate the offspring population O of P';
5) Environmental Selection (lines 7-8): Use environmental selection of AGE-MOEA-II to select N individuals from $P \cup O$;
6) Parameters Updation (line 9): Update parameters $[\mathbf{B}, \mathbf{v}_m, p_s]$ of ARSBX;
7) Repeat steps 3) - 6) until the maximum number of fitness evaluations (NFE_{max}) is reached.

Algorithm 1 MOEA-AP

Require: N, population size; M, number of objectives; D, number of decision variables; NFE_{max}, maximum number of fitness evaluation; $\mathbf{B}$, the rotated matrix; $\mathbf{v}_m$, the mean vector; p_s, probability parameter;
Ensure: P, final population;
1: $P \leftarrow$ Initialization (N);
2: $[FN, S] \leftarrow$ Environmental selection of AGE-MOEA-II (P, N);
3: $NFE \leftarrow N$;
4: **while** $NFE \leq NEF_{max}$ **do**
5: $\quad P' \leftarrow$ Select N parents via binary tournament selection (P, FN, S);
6: $\quad O \leftarrow$ ARSBX & PM $(P', \mathbf{B}, \mathbf{v}_m, p_s)$;
7: $\quad P \leftarrow P \cup O$;
8: $\quad [P, FN, S] \leftarrow$ Environmental selection of AGE-MOEA-II (P, N);
9: $\quad [\mathbf{B}, \mathbf{v}_m, p_s] \leftarrow$ Parameters updation for ARSBX $(P, D, M, NFE, NFE_{max})$;
10: **end while**

In MOEA-AP, ARSBX is applied to generate new individuals, where an adaptive selection strategy is proposed to make use of both SBX and the rotation-based SBX (RSBX). After that, a new parent population P is selected via strategy based on modeling the shape of the non-dominated front using the Newton-Raphson iterative method for roots funding. Readers who are interested in ARSBX and the environmental selection in AGE-MOEA-II could refer to [2] and [3] for more details.

Jiangtao Shen and Junchang Liu are candidate doctor students. Huachao Dong, Xinjing Wang, and Peng Wang are faculty members. This report is written and the competition information is acquired by Jiangtao, the algorithm is developed and tested by Jiangtao and Junchang, and the submitted data is handled by Junchang.

TABLE I: Mean HV values and standard deviations of NSGA-II and MOEA-AP on CitySegMOP1-CitySegMOP15 over 31 independent runs. The best result of each instance is highlighted.

Problem	N	M	D	NFE_{max}	NSGA-II	MOEA-AP
CitySegMOP1	100	2	24	10000	8.9799e-1 (4.33e-3) $-$	9.0066e-1 (1.76e-3)
CitySegMOP2	105	3	24	10000	7.9819e-1 (1.93e-3) $-$	7.9927e-1 (2.12e-3)
CitySegMOP3	105	3	24	10000	8.2143e-1 (4.74e-3) $\approx$	8.2172e-1 (4.61e-3)
CitySegMOP4	120	4	24	10000	6.9729e-1 (1.52e-3) $-$	6.9827e-1 (6.79e-4)
CitySegMOP5	126	5	24	10000	6.5612e-1 (8.83e-4) $\approx$	6.5610e-1 (9.75e-4)
CitySegMOP6	100	2	24	10000	7.7185e-1 (2.94e-4) $\approx$	7.7123e-1 (3.90e-3)
CitySegMOP7	105	3	24	10000	7.3013e-1 (5.32e-3) $\approx$	7.3110e-1 (2.04e-4)
CitySegMOP8	105	3	24	10000	7.3237e-1 (2.49e-4) $\approx$	7.3233e-1 (2.59e-4)
CitySegMOP9	120	4	24	10000	5.7656e-1 (3.40e-4) $\approx$	5.7668e-1 (3.34e-4)
CitySegMOP10	126	5	24	10000	5.4684e-1 (2.15e-3) $\approx$	5.4715e-1 (3.73e-4)
CitySegMOP11	105	3	24	10000	6.8725e-1 (2.97e-3) $-$	6.8882e-1 (1.42e-3)
CitySegMOP12	126	5	24	10000	4.6776e-1 (2.35e-3) $-$	4.7192e-1 (1.09e-3)
CitySegMOP13	132	6	24	10000	4.1650e-1 (7.75e-3) $-$	4.2274e-1 (4.15e-4)
CitySegMOP14	132	6	24	10000	4.3003e-1 (3.48e-3) $-$	4.3244e-1 (8.18e-4)
CitySegMOP15	217	7	24	10000	3.9519e-1 (6.49e-3) $-$	3.9864e-1 (2.85e-4)
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II. Experimental Studies

A. Experimental Settings

1) The proposed MOEA-AP is compared with NSGA-II [4] on the CitySegMOP1-CitySegMOP15;
2) For NSGA-II, the distribution index η_c of simulated binary crossover (SBX) is set to 20, and the crossover probability p_c is set to 1;
3) For ARSBX, the rotated matrix $\mathbf{B}$ is initialized as an identity matrix $\mathbf{I}$, the mean vector $\mathbf{v}_m$ is initialized as $(\mathbf{U}+\mathbf{L})/2$, where $\mathbf{U}$ and $\mathbf{L}$ denote the upper and lower values of each decision variable, respectively, the probability parameter p_s is set to 0.5; the distribution index η_c is set to 2, and the crossover probability p_c is set to 1;
4) For polynomial mutation (PM), the distribution index η_m is set to 20, and the mutation probability p_m is set to $1/D$;
5) The population size of City SegMOP1-SegMOP15 are $[100, 105, 105, 120, 126, 100, 105, 105, 120, 126, 105, 126, 132, 132, 217]$, respectively;
6) The maximum number of fitness evaluations $NFE_{max} = 10000$ for each instance;
7) The experiments are conducted on the PlatEMO [5].

B. Results

TABLE I lists the mean HV values and standard deviations of NSGA-II and MOEA-AP on CitySegMOP1-CitySegMOP15 over 31 independent runs. The best result of each instance is highlighted. The Wilcoxon rank sum test is adopted at a significance level of 0.05. "$+$", "$-$" and "$\approx$" indicate that the results of NSGA-II are significantly better, significantly worse, and statistically similar to the results of the proposed method. From the table, the proposed MOEA-AP shows the best performance on 12 instances out of 15, and NSGA-II performs best on 3 instances. It is obvious that MOEA-AP shows overall better performance on CitySegMOP1-CitySegMOP15 than NSGA-II.

References

[1] Z. Lu, R. Cheng, Y. Jin, K. C. Tan and K. Deb, "Neural Architecture Search as Multiobjective Optimization Benchmarks: Problem Formulation and Performance Assessment," IEEE Transactions on Evolutionary Computation, vol. 28, no. 2, pp. 323-337, April 2024.

[2] L. Pan, W. Xu, L. Li, C. He and R. Cheng, "Adaptive simulated binary crossover for rotated multi-objective optimization," Swarm and Evolutionary Computation 60: 100759, 2021.

[3] A. Panichella, "An improved Pareto front modeling algorithm for large-scale many-objective optimization," In Proceedings of the Genetic and Evolutionary Computation Conference (GECCO '22), Association for Computing Machinery, New York, NY, USA, pp. 565–573, 2022.

[4] K. Deb, A. Pratap, S. Agarwal and T. Meyarivan, "A fast and elitist multiobjective genetic algorithm: NSGA-II," IEEE Transactions on Evolutionary Computation, vol. 6, no. 2, pp. 182-197, April 2002.

[5] Y. Tian, R. Cheng, X. Zhang and Y. Jin, "PlatEMO: A MATLAB Platform for Evolutionary Multi-Objective Optimization [Educational Forum]," IEEE Computational Intelligence Magazine, vol. 12, no. 4, pp. 73-87, Nov. 2017.