Grid-Based Evolutionary Algorithm Assisted by Self-Organizing Map for Multiobjective Neural Architecture Search in Real-Time Semantic Segmentation

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I. Description

In this report, we have proposed a grid-based evolutionary algorithm assisted by a self-organizing map for multi-objective neural architecture search in real-time semantic segmentation, named GrSMEA_NCHU. This is a novel coevolutionary framework, which simultaneously maintains two collaborative and complementary populations. Fig. 1 depicts the flowchart of the overall framework of the proposed GrSMEA_NCHU. In GrSMEA_NCHU, two populations evolve with different optimizers separately. Specifically, Population 1 is mainly responsible for promoting the diversity of the population. Therefore, GrSMEA_NCHU adopts the environmental selection strategy of GrEA [1] to select the solutions for the next generation. Different from Population 1, Population 2 is a complement, which assists in exploring the areas that have not been exploited by Population 1. We use the convergence update strategy of Two_Arch2 [2] as the selection principle for Population 2 to improve convergence on NAS problems. As shown in Fig. 1, the proposed GrSMEA_NCHU begins with the random initialization of two populations, Population 1 and Population 2, with sizes N and $\lceil N^{\frac{1}{m-1}} \rceil^{(m-1)}$, respectively. Then, a self-organizing Map(SOM) is initialized. During the initialization of SOM, we assign each neuron's weight vector a randomly chosen training point from Population 2. In the reproduction phase, two mating pools are formed separately. The mating pool of Population 1 is selected by the mating selection strategy of GrEA. As for Population 2, we utilize the neighborhood relationship information extracted by the SOM to assist in constructing the mating pool [3], [4] . Afterwards, each of the mating pools is used to generate an offspring population by the reproduction operators [5]. Then, both Population 1 and Population 2 are combined with the offspring populations, and further truncated by the environmental selection strategy. In this way, useful information is shared between the two populations. Next, the SOM update strategy is used to iteratively update weight vectors. The above steps are repeated until a termination condition is met. Finally, Population 1 is reported as the final output.

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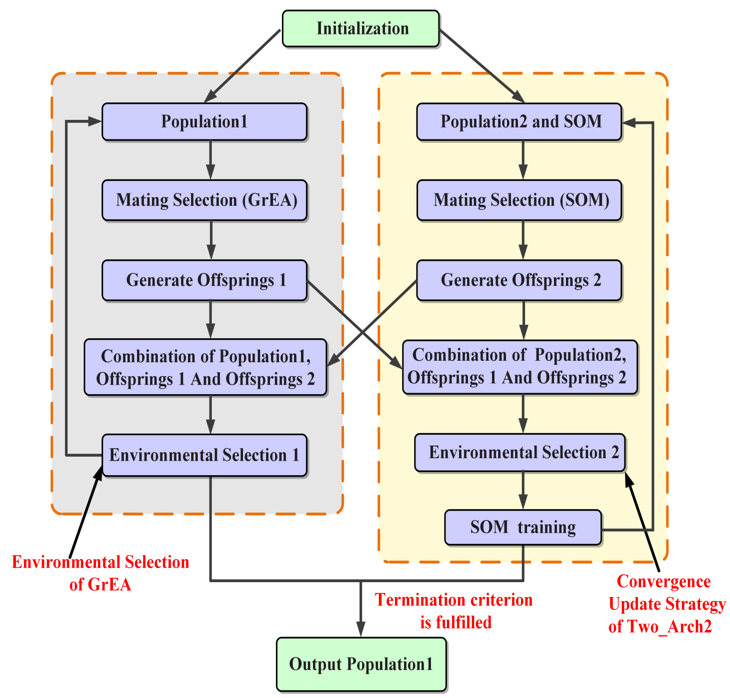

Fig. 1. Flow chart of GrSMEA_NCHU.

TABLE I
HV VALUES OBTAINED BY GrSMEA_NCHU ON CITYSEGMOP

Problem	M	D	GrSMEA_NCHU
CitySegMOP1	2	24	9.0069e-1 (1.60e-3)
CitySegMOP2	3	24	7.9959e-1 (9.05e-4)
CitySegMOP3	3	24	8.2368e-1 (8.47e-4)
CitySegMOP4	4	24	6.9814e-1 (8.18e-4)
CitySegMOP5	5	24	6.5673e-1 (5.00e-4)
CitySegMOP6	2	24	7.7186e-1 (2.53e-4)
CitySegMOP7	3	24	7.3124e-1 (1.49e-4)
CitySegMOP8	3	24	7.3245e-1 (1.80e-4)
CitySegMOP9	4	24	5.7666e-1 (6.27e-4)
CitySegMOP10	5	24	5.4738e-1 (2.65e-4)
CitySegMOP11	3	24	6.8894e-1 (1.17e-3)
CitySegMOP12	5	24	4.7340e-1 (1.07e-3)
CitySegMOP13	6	24	4.2285e-1 (9.43e-4)
CitySegMOP14	6	24	4.3473e-1 (8.95e-4)
CitySegMOP15	7	24	3.9858e-1 (4.89e-4)
$+/-/\approx$			

II. Experimental settings

The proposed GrSMEA_NCHU is implemented in PlatEMO4.6 using a PC with an Intel i7-8700 CPU and 8GB memory.

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