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A Double-population Algorithm Based on NSGA-II ⋆

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Abstract

To maintain the diversity and improve convergence of the NSGA-II, a double-population algorithm based on NSGA-II (DP-NSGA-II) is proposed. In different circumstances, the algorithm produces two offspring population. Through the competition between two offspring populations, the advantage group is selected. A method based on the nondominated sorting method of NSGA-II algorithm is employed to the sort of parent group and new advantage group. L-near distance is used to maintain the diversity of the population. The simulation results show that the proposed algorithm has advantageous on popularity diversity and better performance to converge to true Pareto-optimal front.

Keywords: NSGA-II; Dual-population; L-near Distance; Nondominated Sorting; Pareto-optimal Front

1 Introduction

NSGA-II [1] is one of the most outstanding multi-objective evolutionary algorithms, which are widely used in various fields and has a very important significance in solving practical problems. However, NSGA-II suffers from its ability to deal with the MOP that includes more than three objectives. On the one hand, NSGA-II is easy to fall into local optimum according to a single evolution environment; on the other hand, it has a certain deficiency in maintaining the diversity of the population.

In 2013, Antonio J. Nebro et al. [2] explored the combined use of three different operators in the NSGA-II algorithm. In 2013, Deb et al. [3] proposed an improved adaptive approach for elitist nondominated sorting genetic algorithm for many-objective optimization (NSGAIII). Bandyopadhyay et al. [4] introduced a mutation algorithm to embed in the NSGA-II, which caused the modification of the parts of the original NSGA-II. Du et al. [5] introduced JADE to NSGA-II aiming at refining the search area to maintain the population diversity. Liu et al. [6]

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introduced a chaotic initial population to enhance the local searching ability and avoid becoming trapped in local optima and to obtain high quality solutions.

In this paper, an improved version of NSGA-II is proposed, which we call DP-NSGA-II. DP-NSGA-II uses a fast nondominated sorting approach to classify solutions according to level of non-domination and an L-near distance operator to preserve solution diversity. The simulation results show that the L-near distance approach find much better spread of solutions. The dual-population in different environments produces offspring populations through crossover and mutation, which enables the populations to have better adaptability.

2 Dual-population NSGA-II Based on L-near Distance

2.1 Improvement of NSGA-II

DP-NSGA-II has improvements on NSGA-II. The improvements are as follows.

(1) Convergence: In different circumstances, parent population gives rise to two new offspring populations. The nondominated solutions of the offspring population are compared with that of parent solutions to form an overall nondominated set of solutions, which becomes the parent population of the next generation.

(2) Diversity: To get an estimate of the density of solutions surrounding a particular solution in the population, we calculate the L-near distance of individual. DP-NSGA-II replaces crowded-comparison with L-near distance.

2.2 L-near distance and dynamic selection

(1) L-near distance

L-near distance is calculated as the sum of distance values corresponding to each point and its nearest neighbors. L is defined as the number of nearest neighbors and decided by the probability. The value of L is decided by probability. And the value of L is 1 or 2. If the probability is more than 0.2, L is selected to be 1. Otherwise, L is selected to be 2.

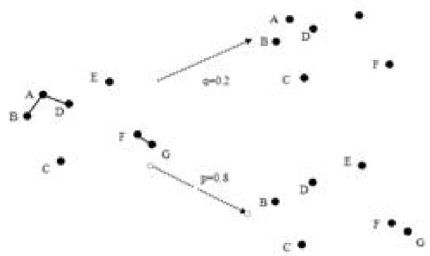


Fig. 1: Eliminating dominated individual dynamically and the number of objectives is more than two

(2) Dynamic selection As shown in Fig. 1, L-near distance is used to eliminate individuals dynamically. The algorithm generates randomly a number between zero and one. If the number is more than 0.2, the L is 2 and the algorithm eliminates the individual A according to 2-near distance, or according to 1-near distance.

2.3 Procedure of DP-NSGA-II

DP-NSGA-II retains the nondominated sorting of NSGA-II and proposes the strategy of dual-population' evolution. Specific steps of DP-NSGA-II are as follows.

Step 1 Initialize the population POP_0, the population POP_0 is sorted according to non-domination.

Step 2 The binary tournament selection, crossover and mutation operators are used to create two offspring populations p_1^t and p_2^t.

Step 3 The two offspring populations p_1^t and p_2^t are merged into one population P^t. The population is P^t sorted according to non-domination. Then, the new population Q^t, which is of size N, is selected from the population P^t.

Step 4 A combined population $R_t = POP_t \cup Q_t$ is formed. The population size is $2N$. The population is sorted according to non-domination. The population is divided into dominated set $F_1, F_2, ..., F_l$.

Step 5 The new population POP_{t+1} is selected from F_1 to F_l based on the L-near distance sorting.

Step 6 If $gen = gen_{max}$, the loop is over; Otherwise, $gen = gen + 1$, $t = t + 1$, go to Step 2.

2.4 Algorithm complexity analysis

Crossover and Mutation are $O(2N)$. Selection of new nondominated population is $O(M(2N^2))$. Nondominated sorting of is $O(M(2N^2))$. Dynamic assignment of L-near distance is $O(M(2N^2))$ $log(2N)$. Sorting on $\prec_n$ is $O(2Nlog(2N))$.

3 Simulation Results

3.1 Test problems

We evaluate the performance of the proposed DP-NSGA-II on a set of test problems [7], which include SCH, KUR, MOP7 as well as series of DTLZ. The test problems are used to compare the performance of DP-NSGA-II with NSGA-II, NNIA [8] and SPEA2 [9]. In this paper, all the above algorithms use the simulated binary crossover (SBX) operator [10] and polynomial mutation [11]. This paper adopts five performance metrics to evaluate algorithm, including GD [12], SP [13], MS [13], IGD [14] and HV [14]. For each of test problems, it needs to be calculated the mean and variance of the experimental data which experiments were repeated 20 times.

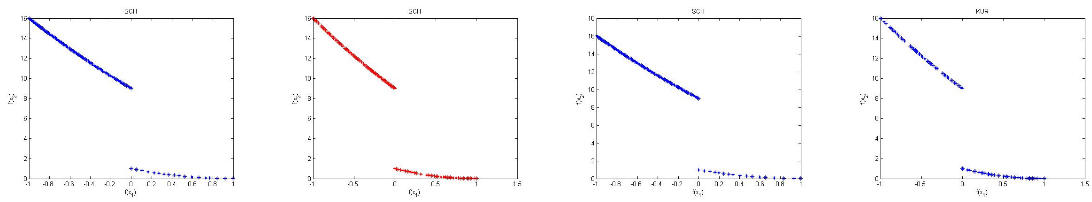
3.2 Simulation result and discussion

Table 1: Simulation result of SCH, KUR, MOP7, DTLZ1 test problems

Problem	Algorithm	SP	MS	IGD	HV
SCH	SPEA2	1.3160e-02	1	2.2349e-03	2.1254e+01
		8.4692e-04	0	1.3834e-04	6.0226e-03
	NSGA-II	5.2553e-02	1	2.5395e-03	2.1210e+01
		3.6881e-04	0	1.0668e-04	5.9205e-03
	NNIA	4.3007e-02	1	2.2207e-03	2.1243e+01
		4.4241e-03	0	9.1639e-05	5.0891e-03
	DP-NSGA-II	1.2766e-02	1	2.2804e-03	2.1258e+01
		1.8761e-03	0	1.0914e-04	1.8044e-03
KUR	SPEA2	5.3405e-02	0.99891992	1.4895e-03	3.7039e+01
		2.4026e-03	3.6544e-05	1.6285e-04	2.3279e-02
	NSGA-II	7.5392e-02	0.99980807	1.8145e-03	3.6947e+01
		1.9811e-02	1.2828e-04	1.8697e-04	6.0226e-03
	NNIA	8.2356e-02	0.99993953	1.5969e-03	3.7038e+01
		1.8466e-02	4.6473e-05	9.8483e-05	1.6838e-02
	DP-NSGA-II	4.0037e-02	0.99989703	1.3443e-03	3.7086e+01
		2.5778e-02	7.1066e-05	1.1576e-04	1.1315e-02
MOP7	SPEA2	1.2219e-02	0.99589206	8.4797e-04	8.7086e-01
		9.3631e-04	2.5651e-04	2.0081e-04	6.5236e-04
	NSGA-II	1.3805e-02	0.99332273	9.4966e-04	8.5811e-01
		2.1977e-03	5.7402e-03	5.3785e-04	2.8622e-03
	NNIA	1.2378e-02	0.99742877	8.4546e-04	8.5368e-01
		2.2151e-03	3.1370e-04	4.3189e-04	6.6729e-03
	DP-NSGA-II	4.3125e-03	0.99521073	8.2107e-04	8.7037e-01
		7.6047e-04	9.6138e-04	2.1037e-04	7.3809e-04
DTLZ1	SPEA2	5.6365e-03	0.98856734	8.4975e-04	7.8432e-01
		6.0873e-04	4.5638e-03	3.8987e-04	2.0453e-03
	NSGA-II	1.5749e-02	1	3.0805e-04	7.6452e-01
		6.9874e-03	0	3.1091e-05	7.6661e-01
	NNIA	1.3710e-02	1	3.4773e-04	2.1243e+01
		1.6586e-03	0	8.5955e-05	4.2709e-03
	DP-NSGA-II	4.2541e-03	0.99821577	2.7588e-04	7.8854e-01
		3.0474e-04	3.7090e-03	1.6504e-05	5.9596e-04

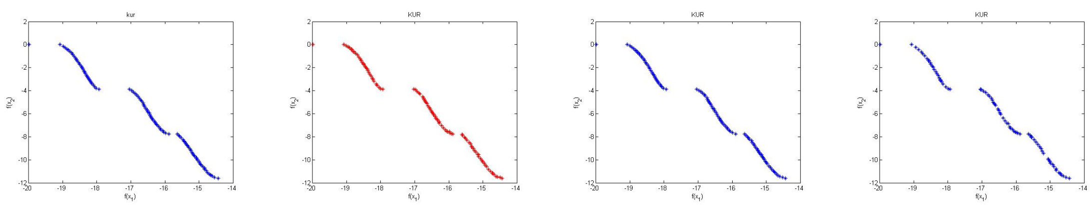
Table 2: Simulation result of DTLZ3, DTLZ6 test problems

Problem	Algorithm	SP	MS	IGD	HV
DTLZ3	SPEA2	1.6348e-02	0.99848632	1.2981e-03	4.0534e-01
		6.8746e-03	5.8756e-04	3.4528e-04	3.4565e-03
	NSGA-II	4.0691e-02	0.99999976	1.1909e-03	3.7460e-01
		6.0169e-04	3.2603e-07	2.6203e-04	5.6363e-03
	NNIA	4.0097e-02	1	1.1946e-03	3.8438e-01
		6.7935e-03	0	1.4153e-04	9.0255e-04
	DP-NSGA-II	1.2376e-02	0.99969181	1.0706e-03	4.1189e-01
		1.1018e-03	2.7616e-04	4.4251e-05	1.7338e-03
DTLZ6	SPEA2	2.5357e-02	0.99848632	4.3254e-03	2.9911e-01
		2.2497e-03	5.8756e-04	1.1004e-03	1.3730e-03
	NSGA-II	5.3102e-02	1	3.8521e-03	2.8972e-01
		7.5723e-03	0	1.1564e-03	3.8051e-03
	NNIA	5.3836e-02	1	3.9917e-03	2.9064e-01
		8.8640e-03	0	7.3053e-04	2.5596e-03
	DP-NSGA-II	1.6847e-02	0.99761798	3.7387e-03	3.0213e-01
		1.9126e-03	1.7155e-03	6.0664e-04	2.3699e-03



(a) (b) (c) (d)

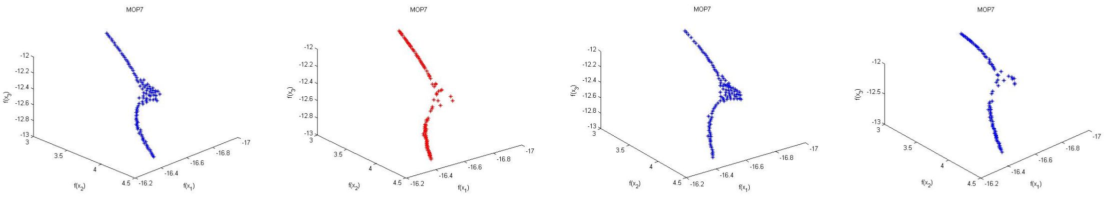
Fig. 2: Nondominated solutions with four kinds of algorithm on SCH



(a) (b) (c) (d)

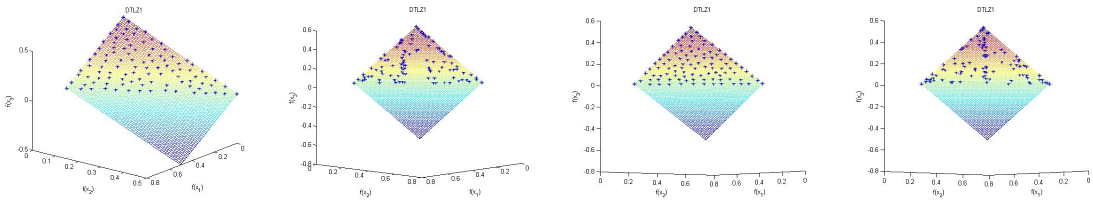
Fig. 3: Nondominated solutions with four kinds of algorithm on KUR

Table 1 and Table 2 show the statistical metric values obtained by four algorithms. Figs. 2 - 7 show non-dominated solutions gotten by four algorithms. DP-NSGA-II performs better than other algorithms in SP. And SPEA2 performs better than NNIA and NSGA-II. NNIA is no better



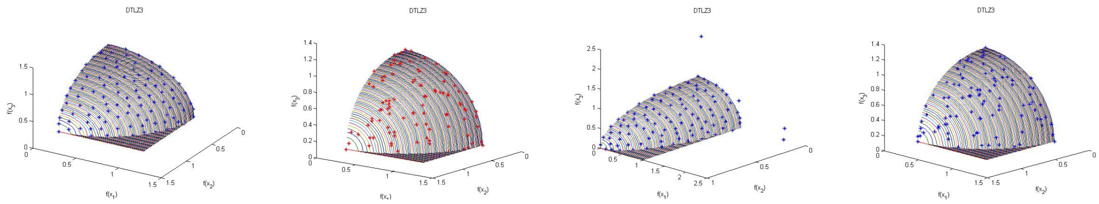
(a) (b) (c) (d)

Fig. 4: Nondominated solutions with four kinds of algorithm on MOP7



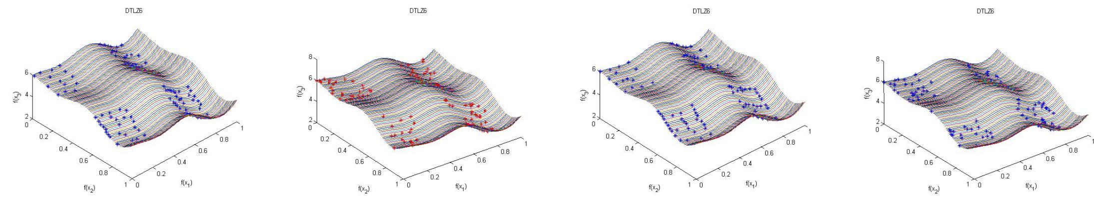
(a) (b) (c) (d)

Fig. 5: Nondominated solutions with four kinds of algorithm on DTLZ1



(a) (b) (c) (d)

Fig. 6: Nondominated solutions with four kinds of algorithm on DTLZ3



(a) (b) (c) (d)

Fig. 7: Nondominated solutions with four kinds of algorithm on DTLZ6

than NSGA-II. In MS, DP-NSGA-II performs well but NNIA performs better than DP-NSGA-II. In GD, DP-NSGA-II performs the best in the entire above test problem. NSGA-II is able to converge a little worse than DP-NSGA-II but better than NNIA and SPEA2. However, for DTLZ4 and DTLZ6 problems, NSGA-II performs no better than NNIA. SPEA2 performs the worst in all the above test problems except DTLZ6. DP-NSGA-II performs better than other algorithms in IGD. For DTLZ4 problem, NSGA-II performs worse than NNIA and SPEA2. However, for other DTLZ problems, NSGA-II performs better than NNIA and SPEA2. SPEA2 performs the worst in series of DTLZ. In HV, DP-NSGA-II performs better than other algorithms. SPEA2 performs a little worse than DP-NSGA-II. However, SPEA2 performs better than NNIA and NSGA-II. NNIA is no better than NSGA-II.

In conclusion, the optimal solutions of DP-NSGA-II shows better performance in the Pareto front of convergence, uniformity, IGD and HV through the above analysis of the four metrics. However, the optimal solutions of DP-NSGA-II show poor performance in the metrics of MS.

4 Summary and Outlook

In this paper, a dual-population NSGA-II based on L-near distance, which combines strategy of the dual-population evolutionary and L-Near Distance. The improved algorithm has a better adaptability, which is not caught in local optimum through the dual-population evolutionary, as well as having a good effect in terms of convergence. Especially, when testing three-dimensional function, this algorithm maintains the diversity of the population better. The simulation results show that DP-NSGA-II outperforms three other algorithms: NSGA-II, NNIA and SPEA2 in terms of finding a diverse set of solutions and in converging near the true Pareto-optimal set. However, DP-NSGA-II reflects certain deficiencies in terms of the broad measure. The future research work will focus on improving the deficiency of DP-NSGA-II in the broad measure. Besides, found in the experimental process, the convergence and the diversity of DP-NSGA-II algorithm have a certain relationship with parameter settings of crossover operator and mutation operator. Therefore, further study of the crossover operator and mutation operator parameters, which is impact on the algorithm, is also a focus of future research work.

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