Research on the Application of Convergence Ratio Parameter in Multi-Objective Evolutionary Algorithm

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Abstract. At present, evolutionary algorithms based on Pareto domination have been extensively studied. Sorting selection method is the most effective environment selection method in this kind of algorithm, which can effectively improve the convergence of the algorithm. But this method is prone to over-convergence of the population. Based on this, this paper proposes a convergence ratio parameter, using a sort selection method to screen a certain proportion of the solution, and the remaining places are selected using a binary game strategy. In this paper, by using this parameter in the KnEA algorithm and comparing it with the original algorithm, it is proved that the convergence ratio parameter can improve the diversity of evolutionary algorithms based on Pareto domination.

1. Introduction

The optimization problem with three or more optimization objectives is called the multi-objective optimization problems (MOPs). At present, the most effective method to solve the multi-objective optimization problem is the evolutionary algorithms (EA) derived from biological genetics, which can also be called the multi-objective evolutionary algorithm (MOEA) [1-3]. In MOEAs, Pareto dominated multi-objective evolutionary algorithm (PDMOEAs) have good performance, rapid development in recent years [4-6], and good research value.

PDMOEAs determine the priority of the solution based on the dominant relationship of the solutions. Higher-priority solutions are retained during the environment selection process. However, on this basis, it ignores the possibility that poor solutions may produce good solutions after cross and variation. Lower-priority solutions cannot survive, reducing the possibility of generating new genes. This makes it possible that the algorithm will tend to be locally optimal and reduces the diversity of the algorithm.

In view of the above problems, a convergence ratio parameter is proposed and applied to a multi-objective evolutionary algorithm based on Pareto domination. Based on the convergence ratio parameter, partial solutions are selected according to the ranking selection method. This part of the solutions has the highest priority, ensuring the convergence of the algorithm. Other solutions that do not use the sort selection method will be filtered according to the binary match strategy. Binary match strategy can balance the diversity of the algorithm. The second part of this article introduces the research motivations and the improvement of the algorithm. The third part introduces the related work of the simulation experiment and the analysis of the experimental results. The fourth part summarizes the main content and conclusion of this article.
2. Multi objective evolutionary algorithm

This section elaborates the research motivation of the convergence ratio parameter proposed in this paper.

At present, several PDMOEAs like KnEA [8] used different two-level sorting methods [7], no longer assigning priorities based on dominant relationships alone, these methods increase the overall priority. Based on the ranking selection strategy, the superior solutions are selected in turn according to the priority, which greatly improves the convergence of the algorithm.

On this basis, KnEA uses a sort selection method for environment selection process. The ranking selection method is to sort the population according to the priority. The solutions with the highest ranking will be retained first. This is an important step to achieve population convergence. However, solutions with lower priority may produce higher priority offspring after cross mutation [9,10]. The new offspring can enrich the population genes and ensure the diversity of the algorithm. Only protect high-priority solutions will lead to a reduction in algorithm diversity.

In order to balance the convergence and diversity of the algorithm, this paper proposes a convergence adjustment parameter (b). We added this parameter into KnEA algorithm and called new algorithm KnEA2.

According to the ranking selection strategy, the ranked solutions can be layered. Starting from the highest priority solution, a certain number of solutions are selected to be retained. All remaining solutions are filtered using the binary match strategy. In the binary game strategy, two solutions are randomly selected. First, their dominance relationship is judged, and the solutions with higher dominance level are retained. If the two dominating levels are the same, it is determined whether they are in K, and the solution in K is retained. If two solutions are in K at the same time, one solution is chosen randomly. Algorithm gives the steps of above process.

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Algorithm Environmental_selection
Input :R(sorted population), K (set of knee points), N(population size), b /* convergence ratio parameter */
1:Q←∅
2:Q←F1 ∪ F2 ∪ ... ∪ Fi-1
3:Q ← Q ∪ (K ∩ Fi)
4:if |Q| > N*b then
5: delete |Q| − N*b solutions from Q which belong to K ∩ Fi and have the minimum distances to the hyperplane
6: end if
7: while |Q|<N do
8: randomly choose a and b from R/Q
9: if a<b then
10: Q←Q ∪ {a}
11: else if b <a then
12: Q←Q ∪ {b}
13: else
14: if a in K then
15: Q←Q ∪ {a}
16: else if b in K then
17: Q←Q ∪ {b}
18: else
19: if and()<0.5 then
20: Q←Q ∪ {a}
21: else
22: Q←Q ∪ {b}
23: end if
24: end if
25: end if
26:end while
return Q
```
3. Experimental setup and result analysis

In order to compare the advantages and disadvantages of the improved algorithm and the original algorithm, this paper uses the test suite DTLZ [11] used in the original KnEA. At the same time, for each test problem in DTLZ test suite, the experimental parameters refer to KnEA algorithm completely.

Through experimental comparison with BiGE [13], NSGAII [14], NSGAIII [15], GrEA [16] and the original algorithm KnEA, it is verified that the improved algorithm KnEA2 achieves the purpose of improving algorithm performance.

3.1. Experiment settings

We consider 2, 4, 6, 8 and 10 targets respectively. The corresponding population size is set to 120, 132, 156 and 275. The cross mutation parameters and the maximum number of iterations under different target numbers are completely consistent with the original KnEA. The parameters of the improved KnEA2 algorithm are shown in Table 1. In addition, the evaluation method IGD [12] (inverted generational distance) used by KnEA was used.

As for the running times and stopping conditions, this experiment runs on the computer of Windows 7 SP1 64 bit operating system configured with 2.30 ghz Intel Core i5-4200u CPU E8500. Each algorithm of each test problem runs independently for 30 times, and all algorithms participating in the experiment use the number of iterations as the termination criterion. The experimental results of DTLZ benchmark suite are shown in Table 2. For a given test problem, in different algorithms, the results with significant performance (the smaller the IGD index is, the better) are represented by gray shadow and bold.

### Table 1. Experimental parameters for DTLZ.

| Problem | Obj.2 | Obj.4 | Obj.6 | Obj.8 | Obj.10 |
|---------|-------|-------|-------|-------|-------|
| DTLZ1   | 0.2   | 0.2   | 0.4   | 0.6   | 0.9   |
| DTLZ2   | 0.2   | 0.4   | 0.6   | 0.6   | 0.8   |
| DTLZ3   | 0.7   | 0.9   | 0.7   | 0.6   | 0.5   |
| DTLZ4   | 0.6   | 0.7   | 0.7   | 0.9   | 0.9   |
| DTLZ5   | 0.1   | 0.2   | 0.2   | 0.2   | 0.2   |
| DTLZ6   | 0.4   | 0.4   | 0.4   | 0.4   | 0.4   |
| DTLZ7   | 0.3   | 0.3   | 0.8   | 0.9   | 0.9   |

3.2. Test results of DTLZ problem set

According to the test results of DTLZ, as shown in Table 2, KnEA algorithm has made great progress after using convergence balance parameters, which is the best in most results. Among the 35 results, the improved algorithm contains 28 optimal results, which shows that the algorithm can be applied to most problems.

Other algorithms, such as BiGE, perform well in DTLZ1, and get the best result when the target number is 2. However, this algorithm performs worse in other test problems.

NSGA2 performs well in test problem 4, including two optimal results when the goal is 4,8, and the optimal solution is obtained when the goal number is 10 in problem 7.

NSGA3 gets the optimal solution when the number of test objects is 10, including the test problem DTLZ 1,2,4,6, which shows that the algorithm has a good effect in high-dimensional space.

The algorithm GrEA has a good performance in testing problem DTLZ2 and problem DTLZ4, and it is the best in some cases. At the same time, when the target number of the algorithm is 8 in DTLZ7, the optimal solution is also obtained.

But according to the optimal number of solutions, the improved algorithm KnEA2 obviously performs best. From the perspective of the test problem, KnEA2 has good results on most problems, but it cannot get an excellent solution on the problem DTLZ4, and performs poorly. In addition to
question 4, the problem 2 is also excellent only when the number of targets is small, and no optimal solution is obtained after the number of targets is increased to 6.

On the contrary, the algorithm performs outstandingly on problem 3,5, and obtains the optimal solution regardless of the number of targets. This shows that KnEA2 has the best optimization effect on problems similar to problem 3,5, and performs poorly on problems similar to problem 2,4. On other issues, the performance is poor when the number of targets is 10, which cannot be optimized efficiently, but the performance is excellent when the number of targets is 2,4,6,8.

From an algorithmic comparison, KnEA2 performs well on most problems, and its overall performance is better than other algorithms. Compared with the experimental results of the original algorithm, it is obvious that the efficiency of the algorithm is improved through improvement. At the same time, by adjusting the convergence balance parameters, in all the experimental results, the improved KnEA2 experimental results are smaller than the original algorithm experimental results. This indicating that the convergence balance parameters do have the function of adjusting the convergence and diversity of the algorithm, it improved the optimization efficiency of the algorithm.

| Problem | M  | BiGE     | NSGAII   | NSGAIII | GrEA      | KnEA      | KnEA2     |
|---------|----|----------|----------|----------|-----------|-----------|-----------|
| DTLZ1   | 4  | 1.9218e+1| 2.7154e+1| 2.2288e+1| 2.2903e+1| 2.1449e+1| (4.37e+0) |
|         |    | (6.60e+0)| (5.90e+0)| (7.31e+0)| (6.21e+0)| (6.63e+0)|           |
|         | 6  | 2.0937e+1| 2.3333e+1| 2.4268e+1| 2.0409e+1| 2.0103e+1| (5.72e+0) |
|         |    | (7.01e+0)| (7.86e+0)| (8.65e+0)| (7.13e+0)| (5.80e+0)|           |
|         | 8  | 1.9358e+1| 2.1804e+1| 2.3004e+1| 2.0529e+1| 1.8921e+1| (6.14e+0) |
|         |    | (1.42e+1)| (6.78e+0)| (6.83e+0)| (6.05e+0)| (6.05e+0)|           |
|         | 10 | 2.2249e+1| 2.3882e+1| 2.3712e+1| 2.2206e+1| 2.0840e+1| (6.14e+0) |
|         |    | (9.63e+0)| (8.55e+0)| (8.63e+0)| (7.02e+0)| (6.79e+0)|           |
| DTLZ2   | 2  | 3.1336e+1| 3.4107e+1| 3.2209e+1| 3.0203e+1| 2.8782e+1| (4.30e+0) |
|         |    | (4.49e-2)| (3.47e-2)| (3.87e-2)| (3.55e-2)| (3.30e-2)|           |
|         | 4  | 4.8150e+1| 5.0490e+1| 4.9432e+1| 4.6905e+1| 4.6773e+1| (3.10e+0) |
|         |    | (4.52e-2)| (2.99e-2)| (3.39e-2)| (3.28e-2)| (3.30e-2)|           |
|         | 6  | 7.3598e+1| 7.4324e+1| 7.1682e+1| 7.1935e+1| 7.1736e+1| (4.80e-2) |
|         |    | (2.85e-2)| (4.77e-2)| (4.57e-2)| (3.17e-2)| (4.80e-2)|           |
|         | 8  | 8.9534e+1| 8.9722e+1| 8.7081e+1| 8.8272e+1| 8.7896e+1| (3.84e-2) |
|         |    | (2.84e-2)| (3.94e-2)| (3.38e-2)| (2.95e-2)| (3.34e-2)|           |
|         | 10 | 9.9735e+1| 9.7496e+1| 9.9861e+1| 1.0075e+1| 1.0068e+1| (2.88e-2) |
|         |    | (4.33e-2)| (3.26e-2)| (3.37e-2)| (3.07e-2)| (2.88e-2)|           |
| DTLZ3   | 2  | 1.6527e+2| 2.0508e+2| 1.7043e+2| 1.6043e+2| 1.5750e+2| (3.02e+1) |
|         |    | (3.93e+1)| (3.43e+1)| (2.94e+1)| (3.02e+1)| (3.02e+1)|           |
|         | 4  | 2.1225e+2| 2.5467e+2| 2.5247e+2| 2.2789e+2| 2.0668e+2| (4.45e+1) |
|         |    | (4.86e+1)| (4.45e+1)| (4.45e+1)| (4.28e+1)| (4.45e+1)|           |
|         | 6  | 2.4700e+2| 3.0407e+2| 3.1939e+2| 2.4793e+2| 2.3720e+2| (5.40e+1) |
|         |    | (5.38e+1)| (6.46e+1)| (4.88e+1)| (4.27e+1)| (5.40e+1)|           |
|         | 8  | 2.7118e+2| 3.1197e+2| 3.6284e+2| 2.7158e+2| 2.6084e+2| (6.34e+1) |
|         |    | (7.64e+1)| (6.16e+1)| (5.37e+1)| (5.05e+1)| (6.34e+1)|           |
|         | 10 | 3.3517e+2| 3.3144e+2| 3.7514e+2| 3.3340e+2| 3.2441e+2| (6.29e+1) |
|         |    | (5.44e+1)| (7.96e+1)| (6.12e+1)| (5.81e+1)| (6.29e+1)|           |
4. Conclusion

Currently, many PDMOEAs use their own methods to ease the selection pressure, but the higher the priority, the faster the algorithm converges. However, the higher convergence leads the diversity of the algorithm cannot be guaranteed. In order to balance the performance of this algorithm, a convergence ratio parameter is proposed in this paper. By using this parameter to improve the similarity algorithm, the performance balance of the algorithm can be guaranteed, thereby improving the efficiency of the algorithm.

In this paper, we improve KnEA, one of these algorithms, and carry out simulation experiments with four other classical algorithms. The results show that the parameter is effective. Compared with
the original algorithm, KnEA2 performs well in most of the problems, and the results are all better than KnEA, which proves that this parameter achieves the effect of improving the performance of the algorithm.

In order to prove that this parameter is suitable for other evolutionary algorithms based on Pareto domination, we will continue to carry out other experiments and improvements.

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References
[1] Deb K. Multi-Objective Optimization using Evolutionary Algorithms. Chichester, UK: John Wiley & Sons, 2001.
[2] Coelo C A C, van Veldhuizen D A, Lamont G B. Evolutionary Algorithms for Solving Multi-Objective Problems. New York: Kluwer Academic Publishers, 2002.
[3] Zheng Jin-Hua. Multi Objective Evolutionary Algorithm and Its Application. Beijing: Science Press, 2007 (in Chinese).
[4] Hui Bai, Jinhua Zheng, Guo Yu, Shengxiang Yang, Juan Zou. A Pareto-based many-objective evolutionary algorithm using space partitioning selection and angle-based truncation. J. Information Sciences, 2019, 478.
[5] Gaurav Dhiman, Vijay Kumar. KnRVEA: A hybrid evolutionary algorithm based on knee points and reference vector adaptation strategies for many-objective optimization. J. Applied Intelligence, 2019, 49(7).
[6] V. Palakonda and R. Mallipeddi. "Pareto Dominance-Based Algorithms With Ranking Methods for Many-Objective Optimization," IEEE Access, vol. 5, pp. 11043–11053, 2017. doi: 10.1109/ACCESS.2017.2716779.
[7] M. Garza-Fabre, G. T. Pulido, and C. A. C. Coello. "Ranking methods for many-objective optimization," in Proc. Mexican Int. Conf. Artif. Intell., 2009, pp. 633–645.
[8] X. Zhang, Y. Tian, and Y. Jin. "A knee point-driven evolutionary algorithm for many-objective optimization," IEEE Trans. Evol. Comput., vol. 19, no. 6, pp. 761–776, Dec. 2015.
[9] R. B. Agrawal, K. Deb, and R. Agrawal. "Simulated binary crossover for continuous search space," Complex Syst., vol. 9, pp. 115–148, Apr. 1995.
[10] K. Deb and M. Goyal. "A combined genetic adaptive search (Gene AS) for engineering design," Comput. Sci. Inf., vol. 26, pp. 30–45, Aug. 1996.
[11] K. Deb, L. Thiele, M. Laumanns, and E. Zitzler. Scalable Test Problems for Evolutionary Multiobjective Optimization. Springer, 2005, pp. 105–145.
[12] Q. Zhang, A. Zhou, and Y. Jin. "RM-MEDA: a regularity model-based multiobjective estimation of distribution algorithm," IEEE Transactions on Evolutionary Computation, vol. 12, no. 1, pp. 41–63, 2008.
[13] M. Li, S. Yang, and X. Liu. "Bi-goal evolution for many-objective optimization problems," Artif. Intell., vol. 228, pp. 45–65, Nov. 2015.
[14] Deb K, Pratap A, Agarwal S, Meyarivan T A. fast and elitist multiobjective genetic algorithm: NSGA-II. IEEE Transactions on Evolutionary Computation, 2002, 6(2): 182-197.
[15] K. Deb and H. Jain. "An evolutionary many-objective optimization algorithm using reference-point-based non-dominated sorting approach, part I: Solving problems with box constraints," IEEE Trans. Evol. Comput., vol. 18, no. 4, pp. 577–601, Apr. 2014.
[16] S. Yang, M. Li, X. Liu, and J. Zheng. "A grid-based evolutionary algorithm for many-objective optimization," IEEE Trans. Evol. Comput., vol. 17, no. 5, pp. 721–736, Oct. 2013.