Crowding Distance based Promising Solution Selection in Surrogate Assisted Asynchronous Multi-Objective Evolutionary Algorithm

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ABSTRACT

This paper proposes an efficient solution selection method in a surrogate-assisted asynchronous multi-objective evolutionary algorithm. Our previous research proposed a novel multi-objective evolutionary algorithm that integrates a surrogate evaluation model with asynchronous approach, named as AELMOEA/D. AELMOEA/D constructs a surrogate model with extreme learning machine (ELM) and generates a promising solution by MOEA/D with a constructed ELM model. A generated promising solution is selected in the order of the indexes of the weighted vector of MOEA/D, and is evaluated asynchronously. In contrast to the previous method, the proposed method considers degree of search progress of each weight vector and selects a promising solution in a region where the search progress is insufficient. To evaluate the degree of the search progress, this study employs crowding distance, which is basically used in NSGA-II. To investigate the effectiveness of the proposed method, we conduct the experiment on a multi-objective optimization benchmark problem. The experimental result revealed that the proposed method can accelerate the convergence speed of the optimization without deteriorating the performance compared with the previous method.

CCS CONCEPTS

• Mathematics of computing → Evolutionary algorithms; **Bio-inspired optimization**; **• Computing methodologies → Continuous space search**; *Parallel algorithms*; Neural networks;

KEYWORDS

Surrogate evaluation model, Extreme Learning Machine, Asynchronous evolution, MOEA/D, Multi-objective optimization

ACM Reference Format:
Tomohiro Harada, Misaki Kaidan, and Ruck Thawonmas. 2018. Crowding Distance based Promising Solution Selection in Surrogate Assisted Asynchronous Multi-Objective Evolutionary Algorithm. In *GECCO '18 Companion: Genetic and Evolutionary Computation Conference Companion, July 15–19, 2018, Kyoto, Japan,* Jennifer B. Sartor, Theo D'Hondt, and Wolfgang De Meuter (Eds.). ACM, New York, NY, USA, Article 4, 2 pages. https://doi.org/10.1145/3205651.3205709

GECCO '18 Companion, July 15–19, 2018, Kyoto, Japan

ACM ISBN 978-1-4503-5764-7/18/07.
https://doi.org/10.1145/3205651.3205709

1 INTRODUCTION

Evolutionary Algorithm (EA) has been applied to many real world problems such as engineering design from the viewpoint of versatility and high search performance. When applying EAs to real world problems, enormous calculation time is required to obtain the optimal solution since the evaluation time of solutions is mostly expensive. To overcome this problem, two typical approaches have been studied, one is surrogate-assisted EA [1], while another is an asynchronous evolution [3].

ELMOEA/D is a recently proposed surrogate-assisted EA, which can reduce the number of actual evaluations until achieving optimal solution. On the other hand, asynchronous EAs can efficiently evolve solutions with different evaluation time since it continuously evolve solutions without waiting other solutions with expensive evaluation time. Our previous research integrated these two approaches and proposed asynchronous ELMOEA/D (AELMOEA/D) [2]. AELMOEA/D can efficiently evolve solution even in the situation where the evaluation time of solutions is expensive and differs from each other.

This research proposes a novel indicator of a promising solution selection in AELMOEA/D by considering the convergence degree of each search region. This aims for accelerating the convergence speed of optimization by intensively searching for areas where search progress is insufficient.

2 AELMOEA/D-CD

In AELMOEA/D, a promising solution is selected in the order of the indexes of the weighted vector of MOEA/D [2]. However, the search ability of AELMOEA/D can be improved if a promising solution is efficiently selected according to the search progress of each search region. In this research, we proposed an extension of AELMOEA/D that considers crowding distance (CD) when selecting a promising solution is named as AELMOEA/D-CD. This paper proposes two different methods with different control strategy to take the balance between the exploitation according to the CD indicator and the exploration widely select a selector vector.

2.1 AELMOEA/D-CD$_{eval}$

In the first method, named as AELMOEA/D-CD$_{eval}$, a promising solution is selected according to the criterion as shown in Eq. (1):

$$UCB1_i = CD_i + C \times \frac{E_{max} - E}{E_{max}} \times \sqrt{\frac{\ln \sum_{k=1}^{N} n_k}{n_i}}, \tag{1}$$

where CD_i is the crowding distance of a solution belonging to the i^{th} selector vector $W_{s,i}$, E_{max} is the maximum number of evaluations, while E is the number of actual evaluations. n_i is the cumulative number of selections of the selector set $W_{s,i}$, while C is the balance parameter. This equation is inspired by the UCB 1 value [4] that calculates how worth each alternative is from its evaluation and the number of selection. A promising solution is selected from the selected vector that has the highest UCB 1 value ($UCB1_i$). In AELMOEA/D-CD$_{eval}$, the priority of the second item decreases as the number of actual evaluations increases, and the importance of CD increases.

2.2 AELMOEA/D-CD$_{HV}$

Unlike AELMOEA/D-CD$_{eval}$ considers the number of actual solution evaluations, the second method, named as AELMOEA/D-CD$_{HV}$, considers the improvement of Hypervolume (HV) of previous and current populations. Eq. (2) shows the criterion to select a promising solution by using the improvement of HV:

$$UCB1_i = CD_i + C \times \frac{HV_{after}}{HV_{before}} \times \sqrt{\frac{\ln \sum_{k=1}^{N} n_k}{n_i}}, \qquad (2)$$

where HV_{after} and HV_{before} are HV of the current and previous population. If the improvement of HV is small, an insufficient area is insufficiently searched according to the CD value. On the other hand, if the improvement of HV is large, all search areas are evenly considered by increasing the weight of the 2^{nd} term.

HV_{before} and HV_{after} are updated every N_s actual solution evaluations. The reference point to calculate HV is updated as the nadir point of the non-dominated solutions of the current population.

3 EXPERIMENT

3.1 Overview

To verify the effectiveness of the proposed AELMOEA/D-CD, we conduct the experiment to compare AELMOEA/D-CD with the original ELMOEA/D and the previous AELMOEA/D without considering the crowding distance on the ZDT1 benchmark. We assess these methods from the viewpoint of the convergence speed with accumulated HV (AHV) [5]. One of the features of AHV is that the speed of convergence of HV is taken into consideration. In this experiment, we use the pseudo master-slave parallel computing environment that refers the computational time model proposed in the previous research [6] with different variance of the evaluation time of solutions (c_v). The parameters setting is same as the previous research [2].

3.2 Result

The median AHV value at the computational time 1.5×10^5 is shown in Table 1. From Table 1, it can be seen that the AHV value of the proposed method is greater than or equal to the previous methods in all benchmark problems. In particular, the significant difference between AELMOEA/D-CD$_{HV}$ and AELMOEA/D is confirmed by the Wilcoxon rank sum test with 5% of significance level, while the signifiant difference between AELMOEA/D-CD$_{eval}$ and AELMOEA/D is also confirmed. From this result, it is revealed that the proposed methods has higher convergence speed than the previous method from the viewpoint of AHV. This is because the proposed promising solution selection based on the crowding distance metric promotes to intensively search an area where the search has not progressed.

Table 1: The AHV value.

c_v	CD$_{HV}$	CD$_{eval}$	AELMOEA/D	ELMOEA/D
0.02	**3649.10***	**3649.10***	3645.30	3636.39
0.05	**3647.88***	**3649.06***	3644.42	3633.96
0.1	**3648.32***	**3648.51***	3644.95	3634.47
0.2	**3647.51***	**3649.63***	3643.87	3624.90

4 CONCLUSION

This paper proposes an efficient promising solution selection method in a surrogate-assisted asynchronous evolutionary algorithm. The proposed method considers the degree of search progress for each weight vector of MOEA/D and selects a region where the search progress is insufficient. To measure the degree of the search progress, the proposed method employs the crowing distance measure. To control the balance between exploration and exploitation of selection, two methods are proposed, AELMOEA/D$_{eval}$ and AELMOEA/D$_{HV}$.

To investigate the effectiveness of the proposed methods, we conducted the experiment on a multi-objective optimization benchmark problem. In the experiment, the proposed methods were compared with AELMOEA/D without the proposed promising solution selection and ELMOEA/D, which is the synchronous approach. The experimental result revealed that the proposed method can accelerate the convergence of the solutions without deteriorating the performance compared with the previous methods. This indicates the proposed promising solution selection based on the crowding distance can intensively search an area where the search is insufficient and it contributes to perform more efficient search.

In the future, we will conduct experiments using not only MOEA/D but also the latest multi-objective optimization methods and will work on further improving the proposed method.

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