클러스터링 기반 차등 진화

신성윤[1*] · 조광현[1] · 조승표[2] · 신광성[3]
[1]군산대학교 · [2](주)에이치브레인 · [3]원광대학교

A Clustering-based Differential Evolution

Seong-Yoon Shin[1*] · Gwang-Hyun Cho[1] · Seung-Pyo Cho[2] · Kwang-Seong Shin[3]
[1]Kunsan Nationl University · [2]Hbrain Co. Ltd. · [3]Wonkwang University
E-mail : {s3397220, gwanghyun}@kunsan.ac.kr / spcho@hbrain.co.kr / waver0984@wku.ac.kr

요 약

우리는 부모 개체 선택을 위한 새로운 데이터 기반 돌연변이 전략, 즉 parapatric 및 cross-generation (TPCDE)이 있는 텐서 기반 DE를 제안합니다.

ABSTRACT

We propose a novel data-driven mutation strategy for parent individuals selection, namely tensor-based DE with parapatric and cross-generation (TPCDE).

키워드
novel data-driven mutation strategy, tensor-based DE, parapatric and cross-generation

Ⅰ. Introduction

Big data, which are digital data with exponential growth and full availability, are recognised with 4Vs characteristics (volume, velocity, variety, and veracity)[1]. To retrieval potential information from big data, an effective solution for solving complex problems has been widely used in big data. However, because of the diversity, vague, and large-scale characteristics of big data, it brings unprecedented challenges for the data-driven method in computational intelligence.

Ⅱ. The tensor-based differential evolution algorithm with parapatric and cross-generational

In this section, the parapatric and cross-generational selection scheme (CGSS) is proposed. The first scheme is to select the parapatric individuals from the current generations; the other is to choose the cross-generational elite individuals. The algorithm mainly improves the parent selection in the mutation strategy and enhances the diversity of the population. The most critical components of the algorithm will be discussed in the following sections.

(1) Individual distribution

The individual is uniformly distributed within the constrained space. During evolution, the individuals will gradually be concentrated around precise solutions. To observe the distribution of individuals during the evolutionary process, the distributions are depicted in Fig. 1, where the axis is the range of individual values, and the individuals connected with the same colour line belong to the same group.

(2) Population presentation based on tensor

After initialisation, the individuals are distributed evenly within different regions. Therefore, the

* speaker

algorithm can explore a promising area. However, in the process of population, the exploration of DE is reduced, because the differences between individuals become smaller, resulting in a lack of sufficient diversity. Therefore, to balance the population diversity, we analyse the components of the individual to find out the difference between them. In this paper, we constructed the population data into a tensor and extracted relevant information through HOSVD. Figure 2 depicts the model of the tensor-based population. The population tensor is a fifth-order tensor, namely generation, individual, boundary partition, strategy, and control parameter.

(3) Description of proposed method

According to the above analysis, the pseudo-code of TPCDE is shown in Algorithm 1, which combines the parapatric-based selection and the cross-generational selection to enhance the performance of DE. In TPCDE, the population tensor is first constructed. The individuals closest to the optimal solution are stored in the elite collection, and the population was clustered into group C by combing the tensor and AP algorithm. Finally, the parent individuals are selected through an adaptive mechanism.

Algorithm 1 The TPCDE algorithm

Input: NP, D, CR, F, and f (.)

Output: best is the best solution of the population

1 Initialise: pop, A, t = 0, iter, k, LP.

2 Evaluate the fitness for each individual.

3 while the halting criterion is not satisfied do

4 best ← select the solution with the smallest fitness.

5 if t % LP == 0 then

6 A ← input A, pop, p in Algorithm 1.

7 A(i) ← tensor A is metricised in all modes.

8 U ← SVD(A).

9 c ← computes the number of dimensions

10 S ← constructed the core tensor

11 C ← S.U{k} is divided into different clusters.

12 end if

13 C← input NP, C, δ in Algorithm 2.

14 for i ← 1 to NP do

15 Select indices r1, r2, r3 from C(i).

16 Perform mutation, crossover, and selection of DE.

17 end for

18 t ← t + 1

19 popg is used to store the population of the g generation

20 if t ≥ iter then

21 Select r1, r2, r3 from popp, popk, popN respectively.

22 pop (i) perform 6-8 steps in Algorithm 1.

23 end if

24 end while

25 Return the best solution best

Ⅲ. 실험

In this subsection, the proposed algorithm's superiority is shown by comparing the TPCDE algorithm and the basic DE algorithm. Furthermore, TPCDE was also compared with three other state-of-the-art DE variants, such as jDE, CoDE, and, OXDE.

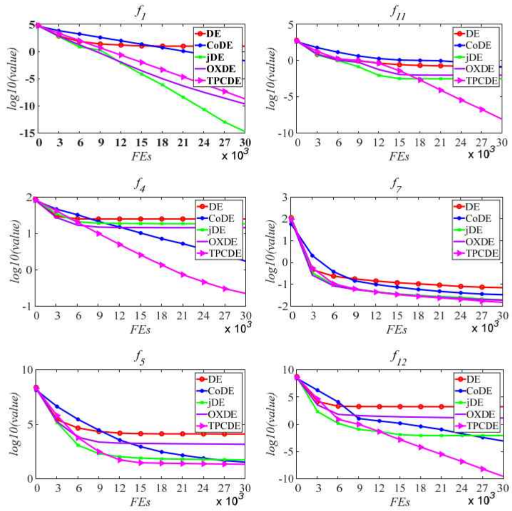

Fig. 1 Evolutionary processes of DE, CoDE, jDE, OXDE and TPCDE (see online version for colours)

Ⅳ. 결론

In this paper, we have proposed a TPCDE selection, which provides proper strategies for the population evolution through data-driven methods. In the process of population evolution, a high order population tensor is reconstructed by the optimised population, and the potential information of population data is extracted by means of data processing.

References

[1] Yi, J-H. and Deb, S. et al. (2018) ‘An improved NSGA-III algorithm with adaptive mutation operator for big data optimization problems’, Future Generation Computer Systems, Vol. 88, No. 1, pp. 571-585.