Differential Evolution with Multi-information Guidance

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ABSTRACT

In this paper, we proposed a novel differential evolution (DE) variant with multi-information guidance. First, based on a rank-based method, the DE population is divided into three groups by using both of the fitness information and position information. Then three distinct combinations of mutation strategy and parameter settings are assigned to these three groups respectively. Last, a neighborhood search operator is conducted with the aim of using the neighborhood information. Experimental results on 22 well-known benchmark functions have shown the effectiveness of our approach.

CCS CONCEPTS

• **Computing methodologies → Search methodologies**;

KEYWORDS

Differential evolution, Multi-information guidance, Neighborhood search

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1 INTRODUCTION

Differential evolution (DE) is one of the most powerful evolutionary algorithms for solving global optimization problems. In recent years, some DE variants with multiple mutation strategies and parameter settings have been shown attractive performance [1]. A salient feature of this kind of variant is that the fitness information of individuals is utilized as a guidance to choose the most suitable mutation strategy and parameter setting. However, we observe that there exists other usable information of individuals except for the fitness information, such as the position information and neighborhood information. There is no doubt that it's an interesting research topic whether the multi-information can be utilized simultaneously.

Along this line of thought, we design a novel DE variant with multiple mutation strategies and parameter settings by attempting to use multi-information guidance. In our recent work, we proposed an enhanced DE variant (RADE) in which a role assignment (RA) scheme was employed [4]. In the RA scheme, the DE population is divided into three groups by considering both of the fitness and position information. However, this current work is different from RADE in that not only the fitness and position information are used, but also the neighborhood information is included. This improved DE variant is abbreviated as MIGDE, and it's evaluated on 22 well-known benchmark functions. The comparison results with seven other algorithms show its effectiveness.

2 OUR APPROACH

For an individual in the DE population, it generally has three different kinds of information: fitness information, position information, and neighborhood information. For the fitness information, it's typically used as a metric to evaluate whether an individual is good or not, while the position information can reflect the characteristics of the fitness landscape and has connection with the fitness information. As for the neighborhood information, the organization relationship among individuals can be inferred by it, and it's also related to the position information. After recognizing the roles of these information, we attempt to utilize them simultaneously. First divide the population into three groups by using both of the fitness and position information, and this is similar to the structure of RADE. But a *rank-based* method is used in our current approach, which is different from the RADE. After that, a neighborhood search operator is produced based on the neighborhood information. The details are describe as follows.

Step 1. Sort all the individuals by fitness value from the best to the worst, and next divide the population in half. Denote the

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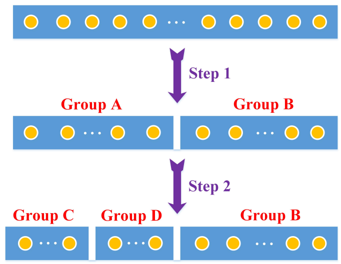

Figure 1: The population division of MIGDE.

half with good individuals as $\boldsymbol{A}$, and denote the other half as $\boldsymbol{B}$. Obviously, the fitness value of any individual in $\boldsymbol{A}$ is better than that of any individual in $\boldsymbol{B}$, and the size of $\boldsymbol{A}$ or $\boldsymbol{B}$ is equal to $PS/2$ (assuming the population size is PS).

Step 2. Mark the best individual in the population as X_b, and then calculate the Euclidean distance from each individual in $\boldsymbol{A}$ to X_b. It can be inferred that X_b is included in $\boldsymbol{A}$, so we only do the calculation for the remaining $(PS/2 - 1)$ individuals in $\boldsymbol{A}$. According to the Euclidean distance, sort the $(PS/2 - 1)$ individuals in $\boldsymbol{A}$ in ascending order. Then divide the $(PS/2 - 1)$ individuals in half, denote the half as $\boldsymbol{C}$ which contains those individuals whose positions are closer to X_b than others, and denote the other half as $\boldsymbol{D}$. Apparently, any individual in $\boldsymbol{D}$ has larger Euclidean distance than that in $\boldsymbol{C}$.

After the above two steps, the population is divided into three groups, i.e. $\boldsymbol{B}$, $\boldsymbol{C}$, and $\boldsymbol{D}$. The division process is also illustrated in Fig.1. As seen, both $\boldsymbol{C}$ and $\boldsymbol{D}$ contains good individuals in terms of fitness value. But the individuals in $\boldsymbol{C}$ are closer to X_b than the ones in $\boldsymbol{D}$ with respect to the position. As for the group $\boldsymbol{B}$, its size is the sum of $\boldsymbol{C}$ and $\boldsymbol{D}$. According to the characteristics of the three groups, the individuals in $\boldsymbol{B}$ are suitable for exploration, while the individuals in $\boldsymbol{D}$ are appropriate for exploitation. The group $\boldsymbol{C}$ can be treated as a middle phase, which serves as the go-between for $\boldsymbol{B}$ and $\boldsymbol{D}$. In short, each group is expected to exhibit distinct search behaviour and complement one another.

To achieve the purposes of the three groups, three distinct combinations of mutation strategy and parameter settings are employed, which are kept the same with RADE. They are listed as follows.

(1) Group $\boldsymbol{B}$: [DE/rand/1, F=0.7 and CR=0.9]
(2) Group $\boldsymbol{C}$: [DE/rand/1, F=0.6 and CR=0.1]
(3) Group $\boldsymbol{D}$: [DE/best/1, F=0.5 and CR=0.1]

As seen, the mutation strategy of group $\boldsymbol{D}$ employs the information of the best individual, which is beneficial for exploitation. And the associated values of F and CR also focus on the exploitation. For the groups $\boldsymbol{B}$ and $\boldsymbol{C}$, the same mutation strategy is selected. Because DE/rand/1 has no bias to any special search directions and chooses new search directions in a random manner. However, the CR value is much different between $\boldsymbol{B}$ and $\boldsymbol{C}$, becuase a small CR value is helpful to derive more information from the target individual, and this is beneficial to exhibit fine search.

As the middle phase, the group $\boldsymbol{C}$ has significant effect on the performance. Therefore, a neighbourhood search operator is conducted for it, which aims to utilize the neighbourhood information to search its vicinity. The following equation is used for this search operator [2].

$$TX_i = r_1 \cdot X_i + r_2 \cdot X_d + r_3 \cdot (X_{b1} - X_{b2}) \tag{1}$$

where TX_i is the trial individual, and X_i is an individual in the group $\boldsymbol{C}$. If TX_i is better than X_i, then X_i is replaced with TX_i. The coefficients r_1, r_2, and r_3 are three mutually exclusive numbers which are randomly chosen from (0, 1), and they have to meet another condition: $r_1 + r_2 + r_3 = 1$. X_d is a random individual in the group $\boldsymbol{D}$, and X_{b1} and X_{b2} are randomly selected from the group $\boldsymbol{B}$.

Table 1: Comparison results of all algorithms.

vs. MIGDE	Better	Similar	Worse
[DE/rand/1, F=0.7 and CR=0.9]	0	5	17
[DE/rand/1, F=0.6 and CR=0.1]	1	8	13
[DE/best/1, F=0.5 and CR=0.1]	0	3	19
[DE/rand/1, F=0.5 and CR=0.9]	1	2	19
RADE [4]	0	10	12
MGBDE [1]	0	3	19
DNSPSO [2]	4	6	12

3 EXPERIMENTAL VERIFICATION

A test suite of 22 well-known benchmark functions is used in the experimnents, which contains 11 unimodal and 11 multimodal functions. The definitions of these functions can be found in [3]. The test dimensionality is set to $D = 30$, and the maximal number of function evaluations is set to $5000 \cdot D$. Seven different algorithms are included for comparison, and all of them have the same population size $PS = 30$. Their other specific parameters are set to the suggested values according to the original papers. The mean and standard deviation values of 30 independent runs are employed to evaluate the optimization performance. Moreover, the Wilcoxon's rank-sum test at the 5% significant level is conducted on the results to obtain a reliable statistic conclusion. Note that the experimental data of the mean and standard deviation values are not provided due to the page limit. From the statistical comparison results in the Table 1, we can see that our approach can achieve better results on most of the test functions, which preliminarily prove the effectiveness of our approach.

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