Elitist Guided Parameter Adaptive Brain Storm Optimization Algorithm

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***Abstract*—With the increasing complexity of continuous optimization problems, the requirement of solving algorithms is higher and higher. To improve the performance of brain storm optimization algorithm, an elitist guided parameter adaptive BSO (EGBSO) is proposed in this paper. The population is sorted in the objective space based on the fitness. The top M individuals are regarded as elitists to guide the ordinary individuals to cluster, which accelerates the convergence speed of the algorithm. The updating mechanism of elite guidance is introduced, which utilizes the cooperation between global optimal individual and elitists to guide the population to a better direction. An adaptive selection parameter is set to make the algorithm more inclined to global search in the early stage and local search in the later stage, balancing the exploration and exploitation capabilities. The proposed EGBSO algorithm and three comparison algorithms are tested on the CEC2017 benchmark test suit, and the experimental results show that the EGBSO has good performance in solving complex optimization problems.**

Keywords*—brain storm optimization, elitist guidance, cooperation, parameter adaptive

I. Introduction

The problem of non-separable is a crucial part of the continuous optimization problem, which has been paid much attention by researchers since it came into being. In the real world, there are certain relationships between the variables of many engineering problems. To find a simple and effective method to solve the complex Non-separable problem is always a difficult problem.

At first, researchers tried to solve Non-separable problems by using some mathematical methods, such as integer programming [1], and branch delimitation [2]. The mathematical model of the problem must be established when the problem is solved by mathematical methods, and it is also required that the mathematical model established is differentiable. However, many engineering problems are difficult to establish mathematical models, that is to say, the mathematical method is highly dependent on the problem to be solved. In view of the limitations of mathematical methods, certain meta-heuristic algorithms have been widely concerned by scholars in recent years. The meta-heuristic algorithms are simple in structure and are easy to be implemented. The most important thing is that meta-heuristic algorithms do not depend on the properties of the problem solved. Common meta-heuristic algorithms are divided into the following three categories.

The first kind of meta-heuristic algorithms is inspired by species evolution theory of Darwin, including Particle Swarm Optimization Algorithm (PSO) [3], Ant Colony Optimization Algorithm (ACO) [4], Artificial Bee Colony Optimization Algorithm (ABC) [5], and Genetic Algorithm (GA) [6]. The second kind of meta-heuristic algorithms simulates physical laws in nature, such as Simulated Annealing (SA) [7], and Water Wave Optimization Algorithm (WWO) [8]. The third kind of meta-heuristic algorithms is certain other emerging intelligent algorithms, such as Differential Evolution Algorithm (DE) [9], and Estimation Distribution Algorithm (EDA) [10].

As one kind of the meta-heuristic algorithms, the BSO algorithm was first proposed in 2011 [11][12]. Compared with other swarm intelligence algorithms inspired by natural phenomena, the BSO algorithm is inspired by the process of human brainstorm. Human beings are the most intelligent animals in the nature. The ideas generated by brainstorm behaviors in human groups are naturally better than those generated by collective behaviors of animals. Therefore, the BSO algorithm has the inherent potential to obtain good ideas. In addition, a learning-based clustering mechanism is introduced in the BSO. Each cluster is regarded as a local optimal area and each cluster center is regarded as a local optimal solution. How to balance the exploration and exploitation ability of the population is a problem worth thinking in swarm intelligence algorithm, and many experts and scholars have made a lot of efforts in recent years. In [13], a BSO algorithm based on discussion mechanism (DMBSO) was proposed, which introduced inter-cluster discussion and intra-cluster discussion to control the global and local searching ability of the algorithm.

In [14], a global-best version was introduced (GBSO), and the performance of the algorithm was improved by combining per-variable updates with fitness-based grouping. In [15], a reinitialization mechanism based on the search process (RGBSO) was introduced and the step size equation was improved to consider the size of the search space, which improved the performance of BSO. In [16], a brain storm optimization algorithm with estimation of distribution (EDBSO) was divided into intra-cluster and inter-cluster discussions in the new individual generation stage. The estimation distribution algorithm was utilized to improve the inter-cluster discussion process of the algorithm. This algorithm effectively avoided falling into the local optimum. A BSO algorithm with orthogonal learning (OLBSO) was introduced in [17]. An exploration orthogonal design engine and an exploitation orthogonal design engine were introduced to utilize the search experience, and the orthogonal decision-making mechanism was used to determine which engine to use in the search process. The mechanisms balanced the exploration and exploitation capacities of the OLBSO. The OLBSO solved the optimization problem of complex functions to some extent. A BSO algorithm with cooperative learning strategy (BSO-CLS) was proposed in [18] to update candidate solutions by linear combination of other solutions and weights obtained from fitness values of other solutions. It had great advantages to solve the problems of large-scale optimization and super parameter optimization.

To improve the performance of BSO algorithm, this paper proposes an elitist guided parameter adaptive brainstorming optimization algorithm. The contributions of this paper are as follows.

- A mutation operator with rotation invariance is proposed to solve the problem of variable non-separable problem. Elitists are utilized to guide the evolution of the individuals to ensure the quality of the population. Multiple individuals are utilized to increase the diversity of the population.
- An elitist guided population division strategy is proposed, in which the elitists are utilized as the centers of clusters and ordinary individuals are guided to the centers.
- A parameter adaptive strategy is proposed to adapt to the early and late stages of population evolution to balance the exploration and exploitation.

The rest of the paper is structured as follows. Section II reviews the original BSO algorithm. Section III introduces the improved BSO algorithm. Section IV carries on the experiment and the result analysis to the proposed algorithm. Section V is the conclusion of this paper.

II. BRAIN STORM OPTIMIZATION (BSO)

BSO is a new intelligent optimization algorithm inspired by human brainstorm behavior, which has been widely concerned by researchers in recent years. The BSO is derived from the human behavior of thinking about problems collectively and consists of four operations.

First, using the k-means method for clustering. All N solutions are clustered into M small areas, refining the search area. The centers of the clusters are calculated, and each center is regarded as a local optimal solution;

Second, to avoid premature convergence and maintain the diversity of the population, a randomly selected cluster center is replaced by a randomly generated individual with a small probability $P_{replace}$;

Third, generating new individuals. To generate $X_{selected}$, a random individual or a center from a random cluster is selected to replace the old individual with a probability P. Alternatively, two clusters or two solutions from two random clusters can be used to replace the old individual with a probability $1-P$. In the above two methods, the probability $P_{one-center}$ and $P_{two-centers}$ are utilized to determine whether to use the centers or the ordinary individuals. The detail is in (1).

$$X_{selected} = \begin{cases} X_i & if\ rand < P_{one-cluster} \\ \omega 1 * X_{i1} + \omega 2 * X_{i2} & otherwise \end{cases} \quad (1)$$

where X_i is a random solution or a center from a random cluster. X_{i1} and X_{i2} are two random solutions or two centers from two random clusters. $\omega 1$ is a random number between 0 and 1, and $\omega 1 + \omega 2 = 1$.

Then, the step size is utilized to update the $X_{selected}$ to strike a balance between exploration and exploitation. It is shown in (2). The generation of X_{new} is shown in (3).

$$\xi = logsig\left(\frac{\frac{T}{2} - t}{K}\right) * rand(0,1) \quad (2)$$

where T is the maximum number of iterations, and t is the current iteration number. K is for changing $logsig()$ function's slope, and rand is a random value between 0 and 1.

$$X_{new} = X_{selected} + \xi * G(\mu, \sigma) \quad (3)$$

where $G(\mu, \sigma)$ is a Gaussian noise with $\mu = 0$ and $\sigma = 1$.

Fourth, selection. The fitness value of the current solution is compared with the fitness value of its parent generation, and the better individual is selected and retained to the next generation.

III. THE ELITIST GUIDED PARAMETER ADAPTIVE BRAIN STORM OPTIMIZATION ALGORITHM (EGBSO)

In this section, two improvements of the BSO algorithm are proposed to improve the performance of the algorithm. The procedure of the EGBSO is shown in Algorithm 1.

A. Elitist Guided Clustering Strategy

To make the center of each cluster more guiding, individuals are ranked in descending order in the objective space according to fitness value in this paper. The individuals in the top M are selected as elitists, that is, the center of each cluster. Each subpopulation can be regarded as a local optimal area and each cluster center as a local optimal solution. According to the M cluster centers obtained, k-means clustering algorithm is used to divide the population into certain sub-populations, and the superior individuals are used to guide the development of the population.

The details are shown in Fig. 1. The red pentacles represent the elitists, and the black dots represent the ordinary individuals. The population is divided into five subpopulations.

Algorithm 1 The EGBSO algorithm

```
Require: N, number of population; M, number of clusters; T, max iteration
randomly generate solution X_i
evaluate the fitness of X_i
while t < T do
    sort individuals in ascending order of fitness values, and take the top M as cluster centers
    cluster N individuals into M clusters
    cluster center disruption
    P = 0.3*e^(1-T/T-t+1)
    for i = 1 to N do
        if rand < P then
            select (4) to generate X_new
        else
            select (5) to generate X_new
        end if
        select X_new or X_i based on their fitness values
    end for
    t = t+1
end while
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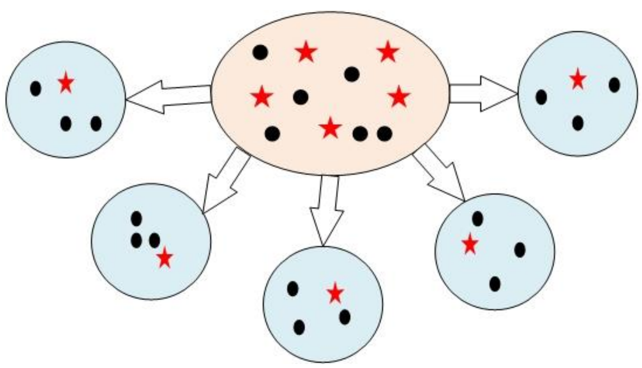


Fig. 1 The population division

B. *Elitist Guided Mutation Strategy*

In this section, two methods are utilized to update the individuals. In the first strategy, the global best and the elitists are introduced to guide the population to a better direction, which accelerate the speed of convergence.

$$X_{new} = X_{best} + 0.5 * \left(X_{gbest} - X_{old}\right) + 0.9 * (X_1 - X_2) \tag{4}$$

where X_{best} is one of the elitists, and X_{gbest} is the global best individual. X_1 and X_2 are two individuals from two different clusters.

The differential step size between the global optimal individual and the current individual is used to generate new individuals. This differential term has a weight of 0.5. Therefore, if the global optimal individual guidance is used, there is a large gap between the old solution and the new solution. The operation leads to missing the global optimal solution and fall into the local optimal solution when the individual is updated. If this proportion is small, the global best guidance can not give full play to the algorithm.

The differential step size of random individuals is 0.9, which is utilized to increase the diversity of the population.

The second strategy is along with the basic BSO.

$$X_{new} = \varepsilon * X_1 + (1 - \varepsilon) * X_2 + stepSize \tag{5}$$

where the ε is a random number between 0 and 1. The $stepSize$ is the ξ in the BSO.

In addition, an adaptive parameter is introduced to determine which strategy can be used to generate new individuals. The parameter P is set in (6).

$$P = 0.3 * e^{1-T/T-t+1} \tag{6}$$

where T is the max iteration, t is the current iteration.

IV. Results and Discussions

To test the performance of the EGBSO, CEC2017 benchmark test suit is utilized to test the EGBSO and the three comparison algorithms. In the CEC2017 test suit, $f1 \sim f3$ are unimodal functions, $f4 \sim f10$ are multimodal functions, $f11 \sim f20$ are hybrid functions, and $f21 \sim f30$ are composition functions.

A. *Benchmark Tests*

The EGBSO is compared with the most advanced variant ALBSO [19], the basic BSO [11], and the SBSA [20]. The SBSA is a population-based intelligence algorithm which is similar to the BSO in the mechanism of population division.

B. *Analysis and Discussion*

The mean error and standard deviation of the four algorithms with the dimension $D = 10$ are shown in Table.1. In general, the results of the EGBSO are superior to the other three comparison algorithms.

The convergence curves of functions $f1, f4, f15, f29$ for the EGBSO and three comparison algorithms is shown in Fig. 2. From the convergence curves, the convergence speed of the EGBSO is faster than the three comparison algorithms.

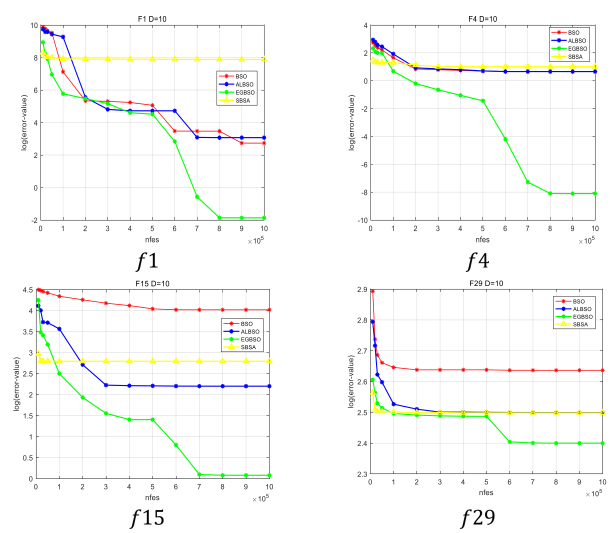


Fig. 2. The convergence curves of four typical benchmark functions

The boxplots of functions $f1, f4, f15, f29$ for the EGBSO and three comparison algorithms is shown in Fig. 4.

Table 1 The results of four algorithms on 29 functions

Fun	BSO		ALBSO		EGBSO		SBSA	
	Mean	Std	Mean	Std	Mean	Std	Mean	Std
F1	5.17E+02	7.30E+02	8.66E+06	4.33E+07	**3.20E+00**	**6.71E+00**	7.66E+07	9.76E+07
F3	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	6.80E-05	1.50E-04	1.92E+03	1.59E+03
F4	3.80E+00	1.50E+00	1.65E+00	1.31E+00	**7.82E-02**	**5.58E-01**	1.27E+01	1.33E+01
F5	4.97E+01	9.85E+00	3.55E+01	1.33E+01	1.70E+01	7.28E+00	**1.31E+01**	**5.04E+00**
F6	2.87E+01	1.04E+01	2.89E+01	9.64E+00	2.46E+00	3.25E+00	**1.03E+00**	**1.02E+00**
F7	9.11E+01	7.41E+00	6.22E+01	2.02E+01	**2.33E+01**	7.59E+00	2.58E+01	**6.64E+00**
F8	1.64E+01	1.48E+01	2.45E+01	9.02E+00	**1.14E+01**	4.18E+00	1.15E+01	**3.66E+00**
F9	2.84E+02	7.96E+01	3.18E+02	1.84E+02	**1.36E+01**	2.19E+01	1.76E+01	**1.59E+01**
F10	8.65E+02	**1.31E+02**	1.07E+03	2.59E+02	8.02E+02	2.86E+02	**3.16E+02**	1.35E+02
F11	4.18E+01	**2.97E+00**	6.30E+01	3.54E+01	**2.19E+01**	1.82E+01	3.17E+01	2.60E+01
F12	7.18E+04	1.80E+04	1.60E+04	3.72E+04	**2.02E+02**	**1.17E+02**	2.82E+05	5.82E+05
F13	1.03E+04	2.63E+03	2.25E+03	3.03E+03	**1.70E+01**	**7.35E+00**	2.09E+03	2.64E+03
F14	2.59E+02	3.04E+02	9.00E+01	8.50E+01	**2.17E+01**	**9.41E-01**	2.85E+01	1.50E+01
F15	1.58E+03	3.32E+01	1.34E+02	1.64E+02	**2.93E+00**	**1.49E+00**	1.16E+02	3.05E+02
F16	1.97E+02	7.48E+01	2.58E+02	1.11E+02	4.25E+01	7.28E+01	**4.11E+01**	**5.61E+01**
F17	2.42E+01	**2.05E+00**	6.91E+01	3.79E+01	3.47E+01	1.58E+01	**1.81E+01**	1.06E+01
F18	2.51E+03	1.66E+03	2.44E+03	3.18E+03	**2.23E+01**	**3.06E+00**	2.04E+03	2.43E+03
F19	4.36E+03	4.59E+03	2.94E+02	1.80E+03	**2.61E+00**	**6.49E-01**	4.80E+02	8.36E+02
F20	5.51E+01	**7.63E+00**	1.29E+02	6.09E+01	4.04E+01	3.90E+01	**1.35E+01**	9.34E+00
F21	**1.54E+02**	7.67E+01	2.00E+02	5.67E+01	1.78E+02	5.36E+01	1.73E+02	**4.81E+01**
F22	**9.51E+01**	7.84E+00	1.06E+02	**5.12E+00**	1.01E+02	9.76E+00	1.13E+02	2.45E+01
F23	3.68E+02	6.66E+00	3.98E+02	3.53E+01	**3.20E+02**	7.90E+00	3.21E+02	**6.25E+00**
F24	4.11E+02	**2.61E+01**	3.71E+02	1.36E+02	**2.94E+02**	1.03E+02	3.11E+02	7.75E+01
F25	4.43E+02	**6.51E-03**	4.29E+02	5.22E+01	**4.24E+02**	2.33E+01	4.32E+02	2.58E+01
F26	**3.67E+02**	2.37E+02	8.12E+02	3.80E+02	4.33E+02	**1.04E+02**	4.05E+02	1.29E+02
F27	4.70E+02	5.61E+01	4.91E+02	5.44E+01	**4.01E+02**	4.65E+01	4.02E+02	**5.86E+00**
F28	4.38E+02	7.55E+01	**4.12E+02**	8.29E+01	4.60E+02	**4.76E+01**	4.38E+02	8.91E+01
F29	3.71E+02	5.43E+01	3.65E+02	8.57E+01	**2.67E+02**	3.68E+01	2.74E+02	**1.98E+01**
F30	4.17E+04	1.88E+04	2.49E+03	3.03E+03	**2.02E+02**	**6.79E-01**	6.95E+04	8.69E+04

Algorithm	Mean Rank
BSO	3.290
ALBSO	2.140
EGBSO	2.100
SBSA	2.470
Crit. Diff. α=0.05	2.128
Crit. Diff. α=0.10	1.834

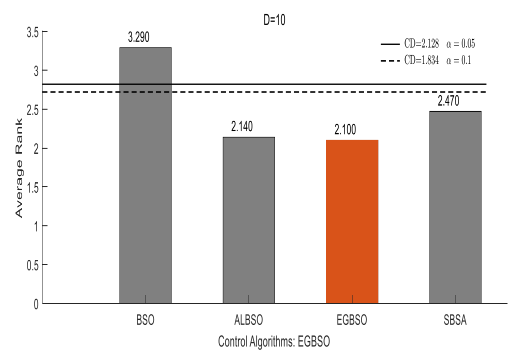
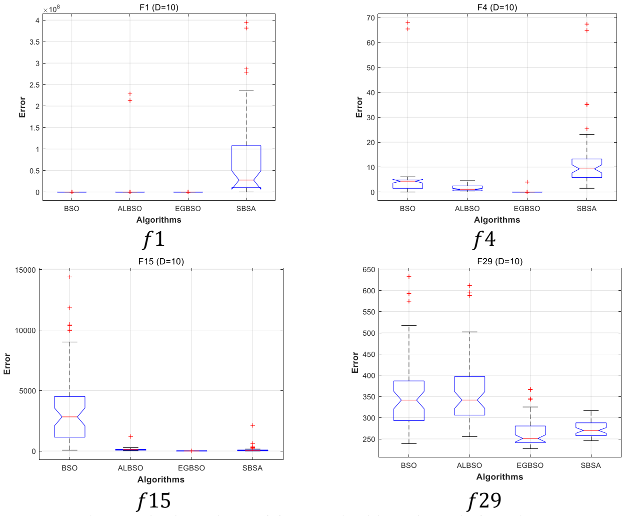


Fig. 3 The result of Friedman test

From the boxplots, the standard variance of the EGBSO is smaller than the three comparison algorithms. The Friedman test was used to analyze the significant difference between the mean errors of the four algorithms. From the statistical results, the average rank of the EGBSO is the smallest of the four algorithms with $\alpha = 0.05$ and 0.1. To test the influence of different strategies on the algorithm, two groups of experiments were conducted, respectively named EGBSO1 and EGBSO2. The second mutation strategy was deleted in the EGBSO1. The first mutation strategy was deleted in the EGBSO2.

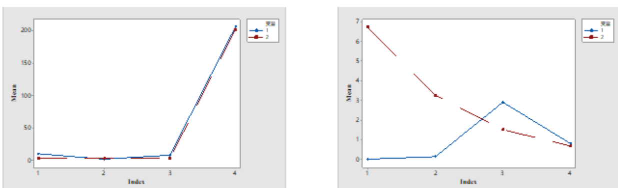


$f1$ $f4$

$f15$ $f29$

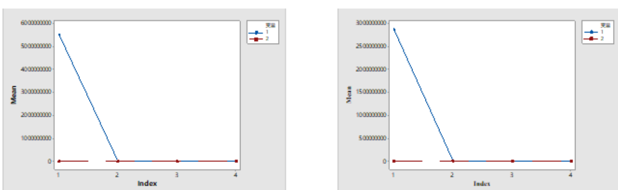
Fig. 4. The boxplots of four typical benchmark functions

The results are shown in Fig. 5 and Fig. 6.



Mean Std

Fig. 5 Comparison results of EGBSO and EGBSO1 in four typical functions



Mean Std

Fig. 6 Comparison results of EGBSO and EGBSO2 in four typical functions

V. Conclusion

In this paper, an elitist guided clustering method is proposed, which takes the elitists as the cluster center. The individuals are guided to gather to the elitists, which promotes the evolution of the population towards a better direction. The method speeds up the convergence speed of the algorithm. An elitist guided multi-individual mutation strategy is proposed, which utilizes the elitists and the global optimal individual to guide the solution to a better direction. In addition, the difference step length of two ordinary individuals are used to increase the population search range, which is helpful to jump out of the local optimal. The selection probability is adaptive adjusted. The algorithm is more inclined to global search in the early stage and local search in the later stage, which balances the exploration and exploitation capability of the algorithm. Experiments on the CEC2017 benchmark test suit show that the proposed EGBSO is effective in solving multi-modal and hybrid problems. In the future, we will add more applications of this algorithm in practical projects.

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