Research Article

An Opposition-Based Group Search Optimizer with Diversity Guidance

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Group search optimizer (GSO) which is an effective evolutionary algorithm has been successfully applied in many applications. However, the purely stochastic resampling or selection mechanism in GSO leads to long computing time and premature convergence. In this paper, we propose a diversity-guided group search optimizer (DGSO) with opposition-based learning (OBL) to overcome these limitations. Opposition-based learning is utilized to accelerate the convergence rate of GSO, while the diversity guidance (DG) is used to increase the diversity of population. When compared with the standard GSO, a novel operator using OBL and DG is developed for the population initialization as well as the generation jumping. A comprehensive set of 19 complex benchmark functions is used for experiment verification and is compared to the original GSO algorithm. Numerical experiments show that the proposed DGSO leads to better performance in comparison with the standard GSO in the convergence rate and the solution accuracy.

1. Introduction

During the past few decades, evolutionary algorithms (EAs) have been developed rapidly and even improved the social development increasingly [1–3]. Diversity of EAs such as Genetic Algorithm (GA) [4], Differential Evolutionary (DE) algorithm [5–7], Ant Colony Optimization (ACO) [8, 9], and Particle Swarm Optimizer (PSO) [10, 11] have been proposed, and they also have been successfully applied in lots of applications in practice. It is noted that most of EAs are developed based on the swarm intelligence coming from the nature world.

Along with this viewpoint, a novel swarm intelligence algorithm, namely, group search optimizer (GSO), inspired by animal behavior [12], has been proven to get more competitive performance in comparison with some typical swarm intelligence algorithms such as PSO when dealing with some complex optimization problems [13]. The GSO algorithm is composed by one initialization operator and three evolutionary operators. Like the other EAs, the initialization operator of GSO is realized based on purely random searching. In

spite of the guidance of animal behavior mechanism, the three operators are also based on random searching to some extent. It is evident that sometimes such random searching mechanism does not come with the optimal solution in the given time. In other words, the defect of the random mechanism leads to long computing time and premature convergence [14–16]. On the one hand, the GSO algorithm is a population-based optimization algorithm, which is prone to suffer from long computing times. On the other hand, random initialization and selection arrives at the best optimization solution only in good luck without any prior information. These two limitations prevent the development of the GSO and restrict the application of GSO in practice.

In this paper, we propose a new evolutionary algorithm, namely, diversity-guided group search optimizer (DGSO), to alleviate the two drawbacks of GSO. The proposed DGSO is realized based on diversity guidance (DG) and a so-called opposition-based learning (OBL) originally coming from neural networks field [17–20]. Diversity guidance is used to increase the diversity of the population of GSO, while opposition-based learning is utilized to accelerate the

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Line# Procedure of GSO algorithm
(1) Begin
(2) Initialization
(3)   Evaluate the fitness of the current member;
(4)   Find a producer;
(5) Producing
(6)   Randomly choose three points based on (1);
(7)   Search the best resource, otherwise stay the current position based on (2);
(8)   If the producer can't search a better area, then change the angle by using (3);
(9) Scrounging
(10)  Randomly choose some group members as the scrounger
(11) Dispersion
(12)  Generate a head angle using (2)
(13)  Obtain a random distance based on (4) and then move to a new point using (5)
(14)  Search a better solution, report the final optimal solution
(15) End

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ALGORITHM 1: Procedure of the GSO algorithm.

convergence speed. Numerical experiments are carried out on several benchmark functions to evaluate the performance of the proposed DGSO.

The structure of the paper is arranged as follows. Section 2 recalls the GSO algorithm. Section 3 presents diversity-guided group search optimizer (DGSO) with opposition-based learning. Section 4 reports the experimental results. At last, some conclusions are drawn in Section 5.

2. Group Search Optimizer Algorithm

Let us recall the original GSO. In the GSO, there are mainly three evolutionary operators: producing, scrounging, and dispersion. The detailed procedure of the GSO is described in Algorithm 1, where n is the dimension; X_i^k is in the i th member at the k th iteration; φ_i^k is a head angle; D_i^k is a unit vector [13].

In the producing operator, the producer scans three points through the following expression [19]:

$$\begin{aligned}
 X_z &= X_p^k + r_1 l_{\max} D_p^k(\varphi^k), \\
 X_r &= X_p^k + r_1 l_{\max} D_p^k\left(\varphi^k + \frac{r_2 \theta_{\max}}{2}\right), \\
 X_l &= X_p^k + r_1 l_{\max} D_p^k\left(\varphi^k - \frac{r_2 \theta_{\max}}{2}\right),
 \end{aligned} \tag{1}$$

where $\theta_{\max}$ is the maximum search angle; $l_{\max}$ is the maximum pursuit distance; r_1 and r_2 are parameters generated under the normally distribution; and r_2 is also a real number in the interval $[0, 1]$.

If the current point changed, the angle is

$$\varphi^{k+1} = \varphi^k + r_2 \alpha_{\max}, \tag{2}$$

where $\alpha_{\max}$ stands for the maximum turning angle [12].

Otherwise the angle is fixed, and the angle is

$$\varphi^{k+a} = \varphi^k, \tag{3}$$

where a is a constant.

In the scrounging operator, we select 80% candidates from the remainder of population.

In the dispersion operator, we used the random walks [22–25]. And the random distance is

$$l_i = a \cdot r_1 l_{\max}. \tag{4}$$

The new point is expressed:

$$X_i^{k+1} = X_i^k + l_i D_i^k(\varphi^{k+1}). \tag{5}$$

3. Diversity-Guided Group Search Optimizer (DGSO) with Opposition-Based Learning

As one of the evolutionary algorithms, GSO is the population-based algorithm, which has the common default; that is, the individuals are selected from a given population randomly generated. To resolve this problem, we used a priori information such as the opposition-based learning, which is applied for making the opposition individuals, and diversity-guided strategy, which is used for improving the diversity of the original GSO. More details of the DGSO are summarized as shown in Algorithm 2.

3.1. Opposition-Based Search Operator. To speed up the convergence of the DGSO, we use a method of opposition-based learning (OBL) [17, 18, 26]. The essence of OBL is using opposite numbers, which would accelerate the convergence of the DGSO and prevent DGSO from suffering expensive computational times which always happens as one weakness in evolutionary algorithm. Let us memorize the basic concepts.

Opposition-based point is as follows [24]: assume $P = (X_1, \dots, X_n)$ is a point, and the dimension is in n , where X_i

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/* Diversity-Guided GSO (DGSO) with Opposition-Based Learning (OBL) */
(1) BEGIN
(2) Initialization (Generate uniformly distributed random population);
(3) Opposition-Based Operator (for Group Initialization);
(4) While the termination condition isn't satisfied
(5)   Diversity-Guided Operator;
(6)   GSO algorithms;
(7)   Opposition-Based Operator (for Generation Jumping)
(8) End While
(9) END

```

ALGORITHM 2: Procedure of diversity-guided GSO (DGSO) with opposition-based learning (OBL).

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Line# Procedure of opposition-based learning operator
(1) Begin
(2)   Generate the population  $P$ 
(3)   for (int  $i = 0$ ;  $i < NP$ ;  $i++$ )
(4)     for (int  $j = 0$ ;  $j < n$ ;  $j++$ )
(5)        $OP_{i,j} = a_j + b_j - P_{i,j}$ ;
(6)   Calculate the fitness value of the  $OP_{i,j}$ 
(7)   Output the some optimal candidates from  $\{P, OP\}$ ;
(8) End

```

ALGORITHM 3: Procedure of opposition-based learning operator.

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#Line Diversity-guided operator procedure
(1) Begin
(2)   if (diversity < dLow)
(3)      $l_{\max} = w_1 * l_{\max}$ ;
(4)   else if (diversity  $\geq$  dHigh)
(5)      $l_{\max} = l_{\max}$ ;
(6)   else if ((diversity  $\geq$  dLow) && (diversity < dHigh))
(7)      $l_{\max} = w_2 * l_{\max}$ ;
(8)   End IF
(9) End

```

ALGORITHM 4: Procedure of diversity-guided operator.

is a real number, $X_i \in [a_i, b_i]$. The opposite point of P is $\tilde{P} = (\tilde{X}_1, \dots, \tilde{X}_n)$, where $\tilde{X}_i = a_i + b_i - X_i$.

Opposition-based optimization (OBL) is as follows [26]: we assume $f(\cdot)$ is the fitness function which is to measure the candidate's fitness value for finding the best candidate solution. According to the above definition, if $f(\tilde{P}) \geq f(P)$, then the point P replaces $\tilde{P}$; otherwise the point is fixed and does not change. Hence, the point P and its opposite point $\tilde{P}$ are evaluated simultaneously to continue the fitter point.

Based on the upper concepts, we embedded the opposition-based operators in the DGSO's initialized group and generation jumping. Algorithm 3 described the procedure of opposition-based learning operator, where P is

the population, $OP_{i,j}$ is the opposite point according to $P_{i,j}$, NP is the population size, and $a_j = \min(x_j^k)$, $b_j = \max(x_j^k)$.

3.2. Diversity-Guided Operator. To alleviate the problem of premature convergence, we use a mechanism of diversity guidance as shown in Algorithm 4. Here the diversity of group (population) is computed by the following formula [27]:

$$\text{diversity} = \frac{1}{|S| \cdot |L|} \cdot \sum_{i=1}^{|S|} \sqrt{\sum_{j=1}^N (p_{ij} - \bar{p}_j)^2}, \quad (6)$$

TABLE 1: Test functions $f_1(x)$ – $f_{11}(x)$.

Function	Definition	Domain	Fitness optimum
$f_1(x)$	$\sum_{i=1}^D x_i^2$	$[-100, 100]^D$	0
$f_2(x)$	$\max_i \{ x_i , 1 \leq i \leq D\}$	$[-100, 100]^D$	0
$f_3(x)$	$\sum_{i=1}^D \left(100(x_i^2 + x_{i+1})^2 + (x_i - 1)^2\right)$	$[-100, 100]^D$	0
$f_4(x)$	$\sum_{i=1}^D (x_i^2 - 10 \cos(2\pi x_i) + 10)$	$[-5, 5]^D$	0
$f_5(x)$	$\sum_{i=1}^D \frac{x_i^2}{4000} - \prod_{i=1}^D \cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$	$[-600, 600]^D$	0
$f_6(x)$	$-20 \exp\left(-0.2 \sqrt{\frac{1}{D} \sum_{i=1}^D x_i^2}\right) - \exp\left(\frac{1}{D} \sum_{i=1}^D \cos(2\pi x_i)\right) + 20 + e$	$[-32, 32]^D$	0
$f_7(x)$	$\sum_{i=1}^D x_i + \prod_{i=1}^D x_i $	$[-10, 10]^D$	0
$f_8(x)$	$\sum_{i=1}^D \left(\sum_{j=1}^i x_j\right)^2$	$[-65.536, 65.536]^D$	0
$f_9(x)$	$\left(\sum_{i=1}^{D-1} f_{100}(x_i, x_{i+1})\right) + f_{100}(x_D, x_1)$ $f_{100} = (x^2 + y^2)^{0.25} \cdot \left(\sin^2\left(50 \cdot (x^2 + y^2)^{0.1}\right) + 1\right)$	$[-100, 100]^D$	0
$f_{10}(x)$	$\sum_{i=1}^D (x_i^2 + 2x_{i+1}^2 - 0.3 \cos(3\pi x_i) - 0.4 \cos(4\pi x_{i+1}) + 0.7)$	$[-15, 15]^D$	0
$f_{11}(x)$	$\sum_{i=1}^{D-1} (x_i^2 + x_{i+1}^2)^{0.25} \left(\sin^2\left(50 \cdot (x_i^2 + x_{i+1}^2)^{0.1}\right) + 1\right)$	$[-100, 100]^D$	0

where $|S|$ is the group size, $|L|$ is the length of the longest diagonal in the search space [26], N is the dimension, p_{ij} is the j th value in the i th member (individual), $\bar{p}$ represents the average point, and $\bar{p}_j$ stands for the j th value of $\bar{p}$. Algorithm 4 described the procedure of diversity-based operator, where $l_{\max}$ is a given number used in formula (1); w_1, w_2 are set as 0.33 and 0.66, individually.

4. Experimental Studies

In this section, we demonstrate the detailed experimental studies of the proposed DGSO. First, we describe test functions and many experimental settings. Second, we compared the DGSO to other algorithms using four comparative analyses, mean and standard deviation, convergence speed, contribution of diversity-guided operator, and contribution of opposite points.

4.1. Experimental Settings

(1) *Test Functions.* We select 19 classical benchmark functions described in [28], where the functions $f_1(x)$ – $f_6(x)$ are selected from CEC 2008 Special Session [29], the functions

$f_7(x)$ – $f_{11}(x)$ were provided from ISDA 2009 Workshop [30], and the functions $f_{12}(x)$ – $f_{19}(x)$ are the hybrid functions based on the previous functions $f_1(x)$ – $f_{11}(x)$ [28]. Test functions $f_1(x)$ – $f_{11}(x)$ are shown in Table 1; test functions $f_{12}(x)$ – $f_{19}(x)$ are shown in Table 2. In the experimental process, we set the population size to 100. For each algorithm, we run 25 times. In the problem size D , we set $D \in \{50, 100, 200\}$. According to [31], MAX_FES is set to $5000 * D$. All of the algorithms are terminated when the MAX_FES is reached.

(2) *Experimental Settings.* We used five different algorithms for comparing: GSO [13], RGSO, OGSO, RDGSO, and DGSO. All of them are based on the GSO algorithm. The only difference is whether they are applied in the manner of initialization and evolutionary operators. More details are described in Table 3. Through all experiments, we set the head angle ϕ_i^k to be $\pi/4$; the maximum search angle $\theta_{\max}$ is π/a^2 , where the value of a is a given number and $\theta_{\max}/2$ is the maximum turning angle (see [13]).

4.2. *Experimental Results.* In this section, we report and analyze the results of the proposed algorithm with some popular algorithms reported in the literatures.

TABLE 2: Test functions $f_{12}(x)$ – $f_{19}(x)$.

	Function	m_{ns}	Domain	FO
$f_{12}(x) = f_9(x) \oplus f_1(x)$	$f_9(x)$ $f_{100} = \left(\sum_{i=1}^{D-1} f_{100}(x_i, x_{i+1}) \right) + f_{100}(x_D, x_1)$ $f_{100} = (x^2 + y^2)^{0.25} \cdot \left(\sin^2 \left(50 \cdot (x^2 + y^2)^{0.1} \right) + 1 \right)$	0.25	$[-100, 100]^D$	0
	$f_1(x)$ $\sum_{i=1}^D x_i^2$			
$f_{13}(x) = f_9(x) \oplus f_3(x)$	$f_9(x)$ $f_{100} = \left(\sum_{i=1}^{D-1} f_{100}(x_i, x_{i+1}) \right) + f_{100}(x_D, x_1)$ $f_{100} = (x^2 + y^2)^{0.25} \cdot \left(\sin^2 \left(50 \cdot (x^2 + y^2)^{0.1} \right) + 1 \right)$	0.25	$[-100, 100]^D$	0
	$f_3(x)$ $\sum_{i=1}^D \left(100(x_i^2 + x_{i+1})^2 + (x_i - 1)^2 \right)$			
$f_{14}(x) = f_9(x) \oplus f_4(x)$	$f_9(x)$ $f_{100} = \left(\sum_{i=1}^{D-1} f_{100}(x_i, x_{i+1}) \right) + f_{100}(x_D, x_1)$ $f_{100} = (x^2 + y^2)^{0.25} \cdot \left(\sin^2 \left(50 \cdot (x^2 + y^2)^{0.1} \right) + 1 \right)$	0.25	$[-5, 5]^D$	0
	$f_4(x)$ $\sum_{i=1}^D (x_i^2 - 10 \cos(2\pi x_i) + 10)$			
$f_{15}(x) = f_{10}(x) \oplus f_7(x)$	$f_{10}(x)$ $\sum_{i=1}^D (x_i^2 + 2x_{i+1}^2 - 0.3 \cos(3\pi x_i) - 0.4 \cos(4\pi x_{i+1}) + 0.7)$	0.25	$[-10, 10]^D$	0
	$f_7(x)$ $\sum_{i=1}^D x_i + \prod_{i=1}^D x_i $			
$f_{16}(x) = f_9(x) \oplus f_1(x)$	$f_9(x)$ $f_{100} = \left(\sum_{i=1}^{D-1} f_{100}(x_i, x_{i+1}) \right) + f_{100}(x_D, x_1)$ $f_{100} = (x^2 + y^2)^{0.25} \cdot \left(\sin^2 \left(50 \cdot (x^2 + y^2)^{0.1} \right) + 1 \right)$	0.5	$[-100, 100]^D$	0
	$f_1(x)$ $\sum_{i=1}^D x_i^2$			
$f_{17}(x) = f_9(x) \oplus f_3(x)$	$f_9(x)$ $f_{100} = \left(\sum_{i=1}^{D-1} f_{100}(x_i, x_{i+1}) \right) + f_{100}(x_D, x_1)$ $f_{100} = (x^2 + y^2)^{0.25} \cdot \left(\sin^2 \left(50 \cdot (x^2 + y^2)^{0.1} \right) + 1 \right)$	0.75	$[-100, 100]^D$	0
	$f_3(x)$ $\sum_{i=1}^D \left(100(x_i^2 + x_{i+1})^2 + (x_i - 1)^2 \right)$			
$f_{18}(x) = f_9(x) \oplus f_4(x)$	$f_9(x)$ $f_{100} = \left(\sum_{i=1}^{D-1} f_{100}(x_i, x_{i+1}) \right) + f_{100}(x_D, x_1)$ $f_{100} = (x^2 + y^2)^{0.25} \cdot \left(\sin^2 \left(50 \cdot (x^2 + y^2)^{0.1} \right) + 1 \right)$	0.75	$[-5, 5]^D$	0
	$f_4(x)$ $\sum_{i=1}^D (x_i^2 - 10 \cos(2\pi x_i) + 10)$			
$f_{19}(x) = f_{10}(x) \oplus f_7(x)$	$f_{10}(x)$ $\sum_{i=1}^D (x_i^2 + 2x_{i+1}^2 - 0.3 \cos(3\pi x_i) - 0.4 \cos(4\pi x_{i+1}) + 0.7)$	0.75	$[-10, 10]^D$	0
	$f_7(x)$ $\sum_{i=1}^D x_i + \prod_{i=1}^D x_i $			

*FO denotes fitness optimum.

(1) *Mean and Standard Deviation.* Two performance indexes, mean and standard deviation, are utilized to measure the performance of different algorithms whose strategies are described in Table 3. Table 4 provides the average values when D is set as 30. As shown in Table 4, the proposed algorithm DGSO performs better than the other algorithms (GSO, OGSO, and RDGSO) in most benchmark functions.

Table 5 summarizes the comparison of DGSO, GSO, and RDGSO with the different dimensions ($D = 50, 100, 200$), respectively. It is evident that DGSO performs better than the other reported algorithms especially in case of the high dimension functions.

(2) *Convergence Speed.* Next we compare the convergence speed between the DGSO and the other four algorithms

TABLE 3: Strategies used in the five GSO algorithms.

Algorithms	Manner of initialization	Manner of evolutionary operators
GSO	Random	Random
RGSO	Random	Opposition-based learning
OGSO	Opposition-based learning	Opposition-based learning
RDGSO	Random	Opposition-based learning and diversity-guided operator
DGSO	Opposition-based learning	Opposition-based learning and diversity-guided operator

TABLE 4: Average fitness values tested on benchmark functions ($D = 30$).

*F	GSO		OGSO		RDGSO		DGSO	
	Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.
F1	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00
F2	0.00E + 00	0.00E + 00	1.43E - 05	1.24E - 05	0.00E + 00	0.00E + 00	2.14E - 03	2.03E - 04
F3	7.99E + 01	5.25E - 01	6.97E + 02	2.86E + 01	6.56E + 01	6.03E - 01	4.55E + 01	3.94E + 01
F4	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00
F5	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00
F6	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00
F7	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00
F8	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00
F9	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00
F10	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00
F11	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00
F12	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00
F13	6.43E + 01	7.47E - 01	2.34E + 01	2.46E + 01	3.93E + 01	8.87E - 01	2.87E + 01	2.49E + 01
F14	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00
F15	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00
F16	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00	1.39E - 158	0.00E + 00	0.00E + 00
F17	3.07E + 01	8.95E - 01	2.14E + 02	2.40E + 01	1.66E + 01	7.42E - 01	9.38E + 00	1.63E + 01
F18	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00
F19	2.15E + 01	2.98E - 01	3.45E + 01	2.64E + 01	1.14E - 02	4.29E - 03	6.96E - 03	4.98E - 03

*F: functions.

including GSO, OGSO, RGSO, and RDGSO. Figure 1 depicts the values of fitness with the increasing of FES [32–34] for $f_1 - f_{19}$. It shows that the convergence speed of DGSO is faster than the other four algorithms.

(3) *Contribution of Diversity-Guided Operator.* Now let us analyze the contribution of diversity-guided operator. For convenience, two algorithms DGSO that used the diversity-guided operator and OGSO that is the opposition-based algorithm without diversity-guided operator are compared.

The experiment results are summarized in Table 6. It is clear that the group (population) of DGSO obtains more diversity in comparison with OGSO in most of benchmark functions.

(4) *Comparison Results of Other Optimization Algorithms.* The proposed DGSO is also compared with some other well-known evolutionary algorithms [21] based on these benchmark functions.

Table 7 describes the comparison results of DGSO and some other algorithms when $D = 100$. As shown in

TABLE 5: Average fitness values tested on benchmark functions with increasing dimension.

Functions		GSO			RDGSO			DGSO		
		dim = 50	100	200	dim = 50	100	200	dim = 50	100	200
F1	Mean	5.00E+00	4.60E+00	5.20E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
	Std.	3.36E+00	0.00E+00	2.17E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
F2	Mean	6.20E+00	5.80E+00	4.40E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	5.00E+00	3.67E+00
	Std.	3.27E+00	0.00E+00	3.91E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	3.61E+00	3.51E+00
F3	Mean	6.60E+00	3.20E+00	4.60E+00	2.40E+00	2.33E+00	2.33E+00	4.80E+00	2.33E+00	4.00E+00
	Std.	1.30E+00	4.76E-02	1.52E+00	3.36E+00	2.08E+00	1.53E+00	0.00E+00	2.52E+00	2.65E+00
F4	Mean	6.40E+00	5.20E+00	3.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
	Std.	2.77E+00	0.00E+00	2.83E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
F5	Mean	5.60E+00	4.40E+00	6.60E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
	Std.	3.65E+00	0.00E+00	2.51E+00	0.00E+00	0.00E+00	0.00E+00	3.49E+00	0.00E+00	0.00E+00
F6	Mean	4.80E+00	2.40E+00	7.40E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
	Std.	3.91E+00	0.00E+00	1.82E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
F7	Mean	3.00E+00	3.00E+00	7.20E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
	Std.	1.00E+00	0.00E+00	2.95E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
F8	Mean	4.00E+00	5.80E+00	3.20E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	6.00E+00
	Std.	2.17E+00	0.00E+00	3.42E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	1.00E+00
F9	Mean	5.40E+00	6.20E+00	4.60E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
	Std.	1.92E+00	0.00E+00	2.88E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
F10	Mean	4.20E+00	3.40E+00	5.20E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
	Std.	3.13E+00	0.00E+00	3.49E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
F11	Mean	3.80E+00	3.40E+00	4.40E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
	Std.	2.51E+00	0.00E+00	2.70E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
F12	Mean	4.20E+00	4.40E+00	2.40E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
	Std.	2.30E+00	0.00E+00	2.61E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
F13	Mean	6.40E+00	5.80E+00	3.00E+00	3.80E+00	1.00E+00	4.67E+00	3.60E+00	3.33E+00	2.67E+00
	Std.	2.86E+00	1.23E-03	2.35E+00	2.59E+00	1.73E+00	5.77E-01	1.82E+00	4.16E+00	3.06E+00
F14	Mean	6.40E+00	4.60E+00	5.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
	Std.	3.65E+00	0.00E+00	2.83E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
F15	Mean	3.20E+00	3.60E+00	4.60E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
	Std.	3.78E+00	0.00E+00	3.36E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
F16	Mean	6.40E+00	6.40E+00	4.60E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
	Std.	3.58E+00	0.00E+00	2.07E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
F17	Mean	4.80E+00	4.80E+00	4.40E+00	2.60E+00	5.67E+00	2.33E+00	5.80E+00	5.33E+00	4.00E+00
	Std.	4.09E+00	1.71E-06	2.97E+00	2.88E+00	1.15E+00	3.21E+00	3.11E+00	2.31E+00	2.00E+00
F18	Mean	3.60E+00	3.60E+00	1.60E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
	Std.	3.51E+00	0.00E+00	1.34E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
F19	Mean	5.00E+00	5.00E+00	3.40E+00	5.40E+00	4.67E+00	3.00E+00	2.80E+00	5.33E+00	3.33E+00
	Std.	2.92E+00	2.12E+01	2.30E+00	3.36E+00	1.53E+00	1.73E+00	1.79E+00	2.08E+00	1.53E+00

Table 7, the proposed DGSO obtains promising results in most of benchmark functions when compared with the other algorithms.

5. Conclusion

In this paper, we proposed a diversity-guided group search optimizer (DGSO) that is realized based on an opposition-based learning method and a diversity-guided operator

mechanism. Experiments are carried out on 19 benchmark functions to demonstrate that the proposed DGSO performs much better results than the other four GSOs including RDGSO, OGSO, RGSO, and GSO.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

TABLE 6: Diversity values of the OGSO and DGSO.

Functions	OGSO		DGSO	
	DIV mean	DIV std.	DIV mean	DIV std.
F1	$1.19E-02$	$3.33E-04$	$2.36E-02$	$8.77E-03$
F2	$1.42E-02$	$3.74E-04$	$1.198E-01$	$1.85E-01$
F3	$2.18E-02$	$2.00E-02$	$9.01E-02$	$1.12E-01$
F4	$1.11E+00$	$6.88E-01$	$1.40E+00$	$1.93E+00$
F5	$4.23E-03$	$3.76E-03$	$2.15E-03$	$1.15E-04$
F6	$1.66E-01$	$1.35E-01$	$3.89E-01$	$6.01E-01$
F7	$8.32E-01$	$6.65E-01$	$1.16E-01$	$3.13E-02$
F8	$5.76E-02$	$2.12E-02$	$2.87E-02$	$1.26E-02$
F9	$1.96E-02$	$1.13E-02$	$5.40E-02$	$7.14E-02$
F10	$1.15E+00$	$1.12E+00$	$1.05E-01$	$3.56E-02$
F11	$1.53E-01$	$1.43E-01$	$9.49E-02$	$8.01E-02$
F12	$1.23E-01$	$1.19E-01$	$1.37E-01$	$2.09E-01$
F13	$3.59E-01$	$6.22E-01$	$5.70E-02$	$7.82E-02$
F14	$2.12E-01$	$2.01E-01$	$3.39E-01$	$1.10E-01$
F15	$5.08E-01$	$4.46E-01$	$1.95E-01$	$1.52E-01$
F16	$1.31E-01$	$1.01E-01$	$4.17E-02$	$3.35E-02$
F17	$1.92E-01$	$1.65E-01$	$6.37E-01$	$1.10E+00$
F18	$4.49E-02$	$3.44E-02$	$5.97E-02$	$6.92E-02$
F19	$1.27E-01$	$3.98E-02$	$9.09E-02$	$2.74E-02$

TABLE 7: Average fitness values tested on benchmark functions.

*F	DGSO		PSO [10]		DE [5]		RGSO [21]	
	Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.
F1	0.00E+00	0.00E+00	$4.69E+05$	$3.22E+04$	0.00E+00	0.00E+00	0.00E+00	0.00E+00
F2	$5.00E+00$	$3.61E+00$	$7.57E+01$	$6.37E+00$	$5.21E+01$	$4.12E+00$	$3.46E-02$	$1.02E-03$
F3	$2.33E+00$	$2.52E+00$	$3.26E+11$	$2.06E+10$	$2.17E+02$	$1.15E+02$	$5.69E+01$	$4.21E-01$
F4	0.00E+00	0.00E+00	$7.41E+02$	$4.96E+01$	$6.38E+02$	$1.01E+02$	$4.3E-06$	$2.31E-05$
F5	0.00E+00	0.00E+00	$9.63E-01$	$6.15E-01$	0.00E+00	0.00E+00	$4.20E+00$	$1.03E-01$
F6	0.00E+00	0.00E+00	$1.96E+01$	$1.83E-01$	$2.28E-10$	$1.33E-10$	$3.72E+00$	$0.48E+00$
F7	0.00E+00	0.00E+00	$1.02E+41$	$2.26E+41$	$2.49E-11$	$1.23E-11$	$4.20E+00$	$2.03E-01$
F8	0.00E+00	0.00E+00	$2.60E+05$	$6.45E+04$	$3.94E+03$	$7.69E+02$	$4.78E+00$	$4.03E-01$
F9	0.00E+00	0.00E+00	$5.84E+02$	$4.06E+01$	$1.14E+00$	$9.30E-01$	$5.13E+00$	$2.46E-01$
F10	0.00E+00	0.00E+00	$5.35E+01$	$3.82E+00$	$5.25E+00$	$1.29E+00$	$3.40E+00$	$1.02E+00$
F11	0.00E+00	0.00E+00	$5.77E+02$	$2.09E+01$	$5.17E+00$	$3.32E+00$	0.00E+00	0.00E+00
F12	0.00E+00	0.00E+00	$3.05E+05$	$2.71E+04$	$6.44E-03$	$9.60E-03$	0.00E+00	0.00E+00
F13	$3.33E+00$	$4.16E+00$	$2.00E+11$	$6.15E+10$	$7.96E+01$	$2.45E+01$	$4.31E+01$	$2.10E-01$
F14	0.00E+00	0.00E+00	$5.35E+02$	$5.24E+01$	$4.67E+02$	$6.71E+01$	$3.27E+00$	$1.04E+00$
F15	0.00E+00	0.00E+00	$3.79E+27$	$6.57E+27$	$4.20E-01$	$5.75E-01$	$5.41E+00$	$1.02E+00$
F16	0.00E+00	0.00E+00	$3.41E+05$	$1.89E+04$	$5.45E+02$	$2.32E-07$	$7.02E+00$	$1.34E+00$
F17	$5.33E+00$	$2.31E+00$	$5.24E+10$	$7.13E+08$	$3.59E+10$	$7.14E+04$	$2.43E+01$	$3.69E-01$
F18	0.00E+00	0.00E+00	$2.05E+05$	$4.85E+03$	$8.25E-02$	$6.47E-02$	$3.21E+00$	$2.68E-01$
F19	$5.33E+00$	$2.08E+00$	$2.13E+10$	$9.43E+09$	$1.93E+01$	$1.53E+00$	$2.15E+01$	$2.98E-01$

*F: functions.

FIGURE 1: Continued.

FIGURE 1: Continued.

FIGURE 1: Convergence results for test functions f_1 – f_{19} .

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