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Improved Grey Wolf Algorithm for Optimization Problems

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Abstract: *Grey wolf algorithm (GWA) is a novel metaheuristic that imitates the behaviour of grey wolves. It mimics the hunting mechanism and leadership hierarchy of grey wolves. It is robust and reliable optimization technique for real life applications. An improved version of GWA (IGWA) is proposed in this paper. The improved version of GWA incorporates the novelty in position updation concept. The performance of IGWA is tested on six benchmark test functions. The proposed approach is also compared with recently developed techniques. Experimental results depict a promising performance of the proposed algorithm and better convergence power than the existing GWA.*

Keywords: *Metaheuristic, Grey wolf algorithm, Optimization*

1. INTRODUCTION

In last few years, it has been observed that metaheuristic algorithms have also been used to solve the combinatorial problems. These are popular among the exiting optimization techniques due to their simplicity, flexibility and local optima avoidance [1]. These are generally divided into two major groups: trajectory-based and population-based. The former one uses a single candidate solution which is improved during the search process. The well-known example of this category is Simulated Annealing [2]. The latter one uses a set of candidate solutions. The candidate solutions are improved during the search process. The main advantages of population-based metaheuristic algorithms over trajectory-based metaheuristic algorithms are sharing the information among candidate solutions and better exploration property [1, 3]. Some of the important population-based metaheuristic algorithms are genetic algorithm (GA) [4], harmony search algorithm (HS) [5, 6], ant colony optimization (ACO) [7], particle swarm optimization (PSO) [8] and gravitational search algorithm (GSA) [9].

Grey Wolf Algorithm (GWA) is a novel population-based metaheuristic algorithm, which is proposed by Mirjalili et al. [1]. It mimics the social leadership and hunting behavior of grey wolves. It has several advantages over the existing metaheuristic algorithms such as [3, 10]: 1) It is simple to implement, 2) It can maintain the information about the search space and keeps the best solution obtained, 3) It has fewer parameters for fine tuning, and 4) It is a derivative-free algorithm. Due to these properties, the performance of GWA is better than existing population-based metaheuristic techniques. It's performance depends heavily upon the two control parameters i.e. A and C. These parameters are responsible for balancing the exploration and exploitation. In this paper, the modification in the value of C is proposed. It changes dynamically during the course of iterations thereby speeding up the convergence process. The proposed approach is tested over six well-known benchmark test functions. The performance of the proposed approach is compared with original version of GWA, PSO, and GSA.

The remainder of this paper is structured as follows. Section 2 describes the improved GWA. The experimental results are presented in Section 3. Section 4 presents the conclusions.

2. IMPROVED GREY WOLF ALGORITHM

The proposed improved grey wolf algorithm is described in this section. First, a brief description of the GWA is mentioned. Thereafter, modification proposed in the GWA is stated.

2.1 GREY WOLF ALGORITHM

Grey wolf algorithm (GWA) is a novel metaheuristic algorithm which is inspired from the nature of grey wolves. It mimics the social hierarchy and hunting behavior of grey wolves [3]. The grey wolves are classified into four main groups such as alpha (α), beta (β), delta (δ), and omega (ω) wolves. The α wolves are leading wolves. They take the important decisions during the hunting process. They also track other wolves in the group to maintain the social equality. The second level of dominated wolves in the group are β wolves. The β wolves are the consultants of α wolves and provide the guidance under different

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circumstances. When α wolves die or become old, they are upgraded to α wolves. The δ wolves control the ω wolves and provide the information to α and β wolves. The lowest level on wolves' hierarchy is ω wolf. They may be children of the group. The hunting process consists of three main steps. The first step is searching and tracking the prey. Thereafter, grey wolves are encircling and harassing the prey until it stops movement. The last step is attacking on the prey. The GWA is mathematically modeled as follows [1, 10].

1. Community Hierarchy: The fittest solution is considered as α wolf. The second and third best solutions are depicted by β and δ wolves respectively. The remaining candidate solutions are depicted as ω wolves. The optimization process is guided by α, β and δ wolves. The ω wolves follow them.

2. Encircling the prey: The grey wolves are encircling the prey. This process is articulated using the following equations:

$$X(t+1) = X_P(t) - A \cdot Dist \tag{1}$$

Here

$$Dist = \left| C \cdot X_P(t) - X(t) \right| \tag{2}$$

where $Dist$ represents the distance between the position of prey (X_P) and a grey wolf (X). t is the current iteration. $X_P(t)$ represents the position vector of prey. A and C are control coefficients which are computed as follows:

$$A = 2av \cdot rand_1 - av \tag{3}$$

$$C = 2 \cdot rand_2 \tag{4}$$

The value of av is linearly decreased from 2 to 0 during the iterations. $rand_1$ and $rand_2$ are random variables ranged from 0 to 1.

3. Hunting the prey: The best candidate solutions (α, β and δ wolves) have adequate awareness about the prey position. These are used to renew their positions based on the position of the best search agents. The hunting behavior is described by the following equations.

$$D_{alpha} = \left| C_1 \cdot X_{alpha} - X \right| \qquad D_{beta} = \left| C_2 \cdot X_{beta} - X \right|$$
$$D_{delta} = \left| C_3 \cdot X_{delta} - X \right| \tag{5}$$

$$X_1 = X_{alpha} - A_1 \cdot D_{alpha} \qquad X_2 = X_{beta} - A_2 \cdot D_{beta}$$
$$X_3 = X_{delta} - A_3 \cdot D_{delta} \tag{6}$$

$$X_3 = \frac{X_1 + X_2 + X_3}{3} \tag{7}$$

4. Attacking the prey: This step represents the exploitation power of algorithm. It is performed by linearly decreasing the value of av from 2 to 0. The value of A should be less than 1 is used to force the wolves to attack on the prey [1].

5. Searching for the prey: This step represents the exploitation power of algorithm. The grey wolves are diverging from each other to search the best prey. To avoid the algorithm to be stuck in local optima, the value of A should be greater than 1 is used to compel the wolves to explore for a better prey.

2.2 PROPOSED MODIFICATION IN GREY WOLF ALGORITHM

The two control parameters, A and C, which are introduced in the step 2 of GWA. The A parameter is used to balance the exploration and exploitation power of GWA.

The other important control parameter is C that influences the exploration process. From equation (2), It has been observed that value of C indicates the weight of the prey in distance computation [11]. If the value of C is greater than 1, it emphasizes the effect of prey's weight, otherwise it reduces the effect. Based on this fact, the novel modification has been proposed in the control parameter C. This proposed approach improves the exploitation of GWA. The value of C changes dynamically with number of iterations and expression is given below:

$$C = 2 \cdot rand_2 - \left(av/2 \right) \tag{8}$$

The modified grey wolf algorithm (MGWA) follows the basic steps of GWA. The proposed equation is introduced in step 2. The equation (2) is replaced with the proposed equation (8). Figure 1 shows the steps of MGWA.

3. EXPERIMENTAL RESULTS AND DISCUSSION

3.1 BENCHMARK TEST FUNCTIONS

To demonstrate the performance of MGWA, six different benchmark test functions are used. These are categorized into two groups: unimodal and multimodal. The unimodal test functions are *Sphere* (F_1), *Schwefel* (F_2), and *Rosenbrock* (F_3). The multimodal test functions are

Griewank (F_4), *Ackley* (F_5), and *Rastrigin* (F_6). These functions are taken from the latest competition on single objective optimization problems at CEC 2013 [12]. Figure 2 shows the 2-D representation of benchmark test functions. The global minimum value of these benchmark functions is zero [12]. Each benchmark test function is tested for 30 independent runs.

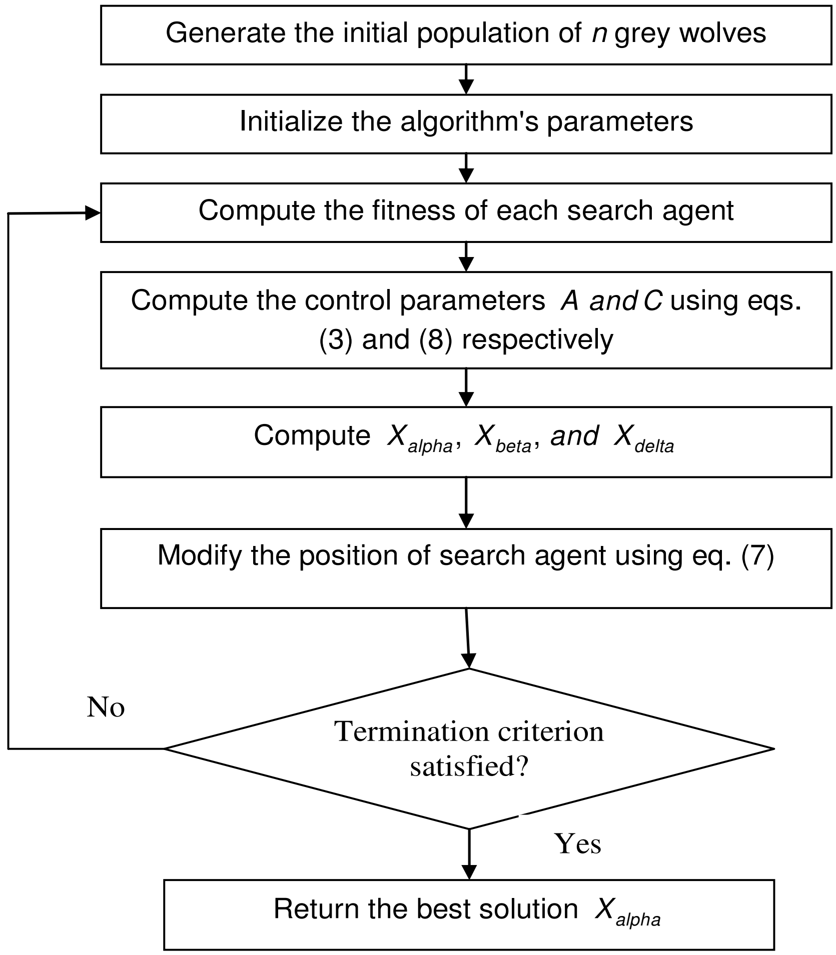
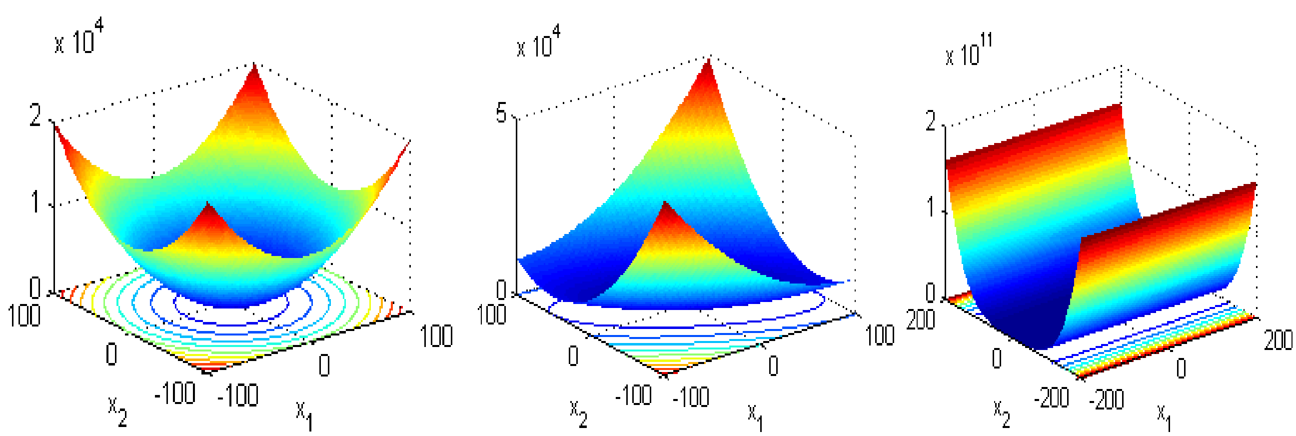


Fig. 1. Flowchart for modified grey wolf algorithm.



(F₁) (F_2) (F_3)

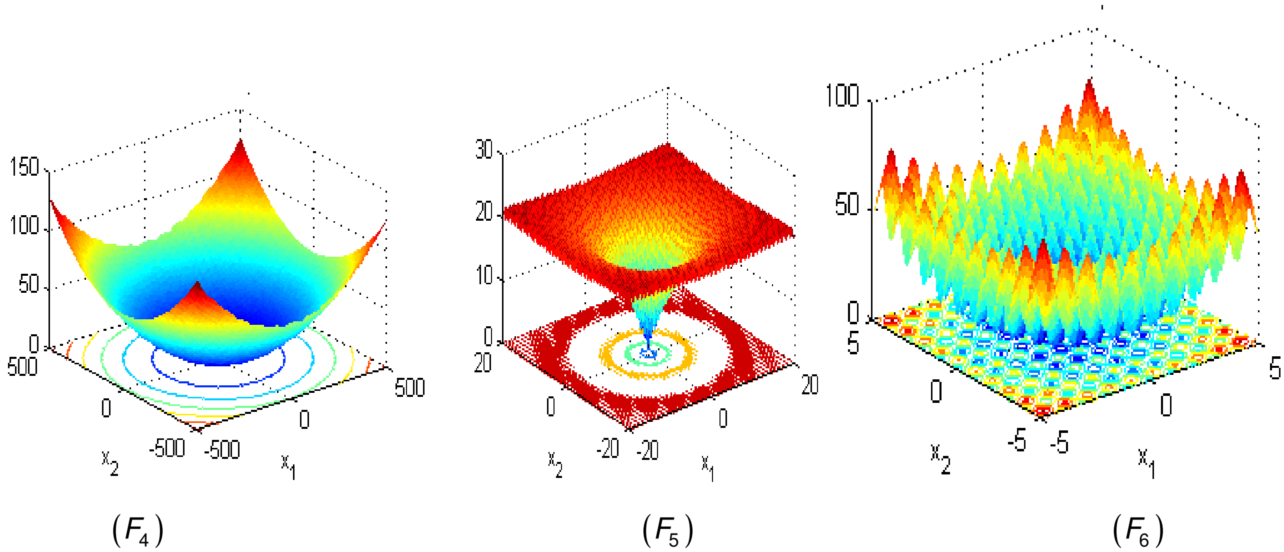


Fig. 2. Two-dimensional representation of benchmark test functions.

3.2 COMPARTIVE EXPERIMENTS ON BENCHMARK PROBLEMS

The performance of proposed approach (MGWA) is compared with original version of GWA and two well-known metaheuristic techniques as PSO and GSA. For the above-mentioned algorithms, the population size and maximum number of iterations are set to 30 and 500 respectively. The other parameters of GWA [1], PSO [8] and GSA [9] are set as they are in their original papers. These algorithms are run 30 times for each test function. The mean and standard deviation values are reported in tables. The values of test functions for GSA and PSO are quoted from [1].

Tables 1 and 2 depict the comparison of the proposed MGWA with above-mentioned existing techniques for unimodal and multimodal test functions respectively. The results reveal that the proposed MGWA has significant performance improvement over the existing GWA. MGWA performs better than other competitive algorithms.

TABLE 1: Results of Unimodal Benchmark Test Functions

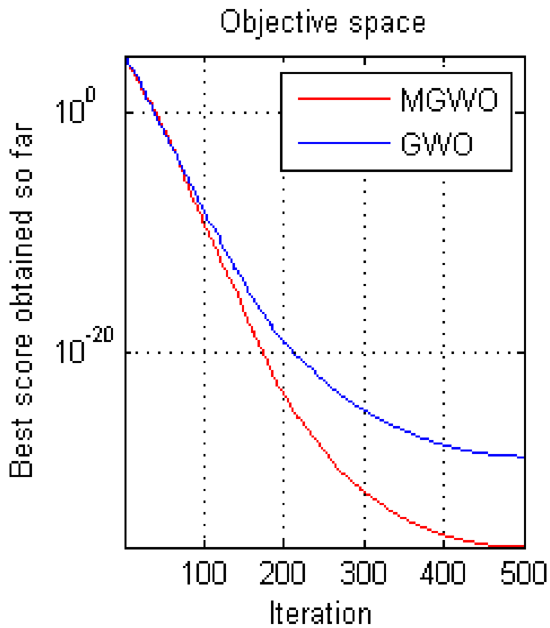
	GSA	PSO	GWO	MGWO
Sphere	2.53E-16 (9.67E-17)	1.36E-04 (2.02E-04)	6.59E-28 (6.34E-05)	1.25E-37 (1.99E-37)
Schwefel	8.96E+02 (3.18E+02)	7.01E+01 (2.21E+01)	3.29E-06 (7.91E+01)	2.90E-10 (3.29E-10)
Rosenbrock	6.75E+01 (6.22E+01)	9.67E+01 (6.01E+01)	2.68E+01 (6.99E+01)	2.66E+01 (6.52E-01)

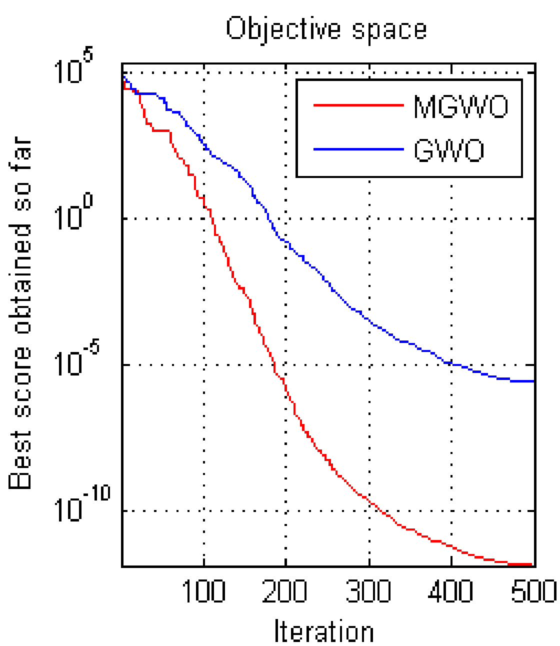
TABLE 2: Results of Multimodal Benchmark Test Functions

	GSA	PSO	GWO	MGWO
Griewank	2.77E+01 (5.04E+00)	9.21E-03 (7.72E-03)	4.49E-03 (6.65E-03)	0.00E+00 (0.00E+00)
Ackley	6.21E-02 (2.36E-01)	2.76E-01 (5.09E-01)	1.06E-13 (7.78E-02)	2.43E-14 (3.43E-15)
Rastrigin	2.59E+01 (7.47E+00)	4.67E+01 (1.16E+01)	3.10E-01 (4.73E+01)	0.00E+00 (0.00E+00)

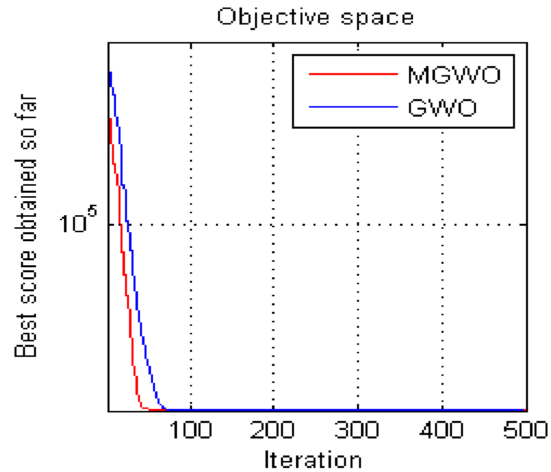
Figure 3 shows the convergence characteristics of GWA and MGWA in terms of the optimal function solution obtained from each algorithm versus the number of iterations. From the convergence curves, we can conclude that MGWA outperforms GWA. MGWA converges fast and prevents the solution being trapped in the local optima.

(F_1)

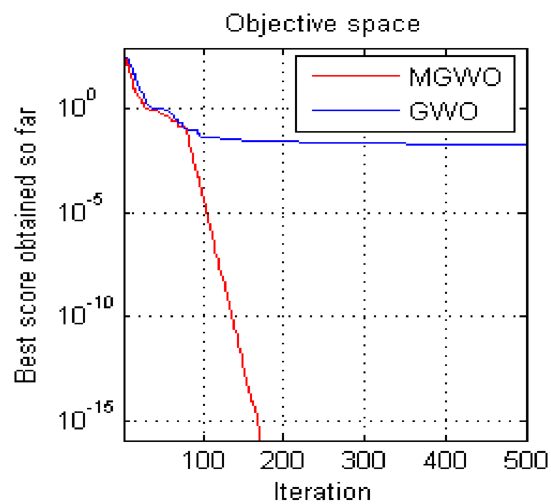




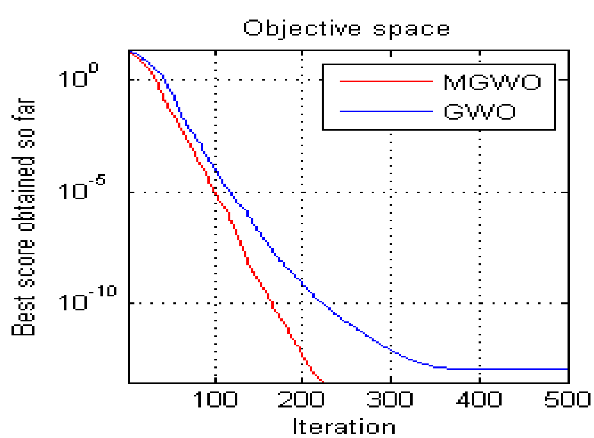
(F_2)



(F_3)



(F_4)



(F_5)

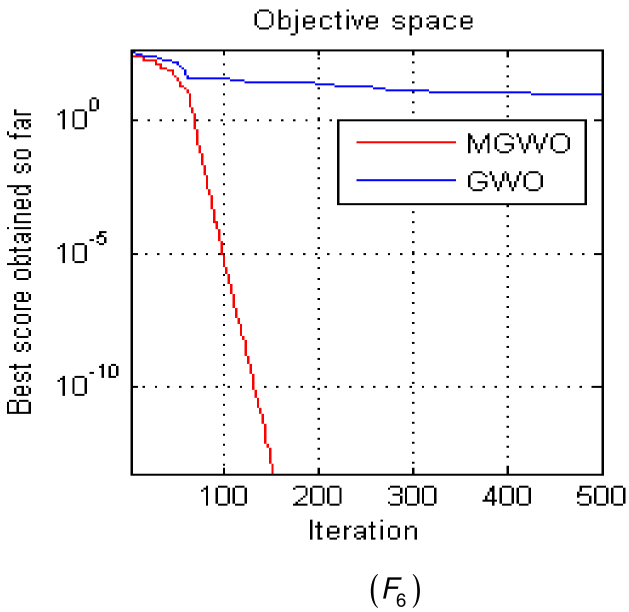


Fig. 3. Convergence characteristics of GWA and MGWA over benchmark test functions.

4. CONCLUSIONS

The paper proposes a modified grey wolf algorithm which utilizes the effect of control parameter in the exploitation process. It has been tested on six benchmark test functions. Experimental results show that the proposed approach performs better than the GWA, PSO and GSA. It has also been experimentally validated that the MGWA has better convergence than GWA.

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