A New Method Based On Modified Shuffled Frog Leaping Algorithm In Order To Solve Nonlinear Large Scale Problem

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Abstract: In order to handle large scale problems, this study has used shuffled frog leaping algorithm. This algorithm is an optimization method based on natural memetics that uses a new two-phase modification to it to have a better search in the problem space. The suggested algorithm is evaluated by comparing to some well known algorithms using several benchmark optimization problems. The simulation results have clearly shown the superiority of this algorithm over other well-known methods in the area.

Index Terms: shuffled frog leaping algorithm, evolutionary algorithms, nonlinear large scale problems

1 INTRODUCTION

SINCE there are many deficiencies in conventional methods such as linear programming and dynamic programming, they can not solve nonlinear multi-objective optimization problems. Theses methods may encounter many difficulties which exist in complex nonlinear problems such as trapping in local optima, slow convergence, differentiability, etc. [1]; also they can not find the optimum solutions when the optimization problem involves many local optimal. Artificial intelligence methods become prevalent in the last two decades. Heuristic and meta heuristic algorithms, artificial neural networks, etc. are some examples of artificial intelligence methods. Meta heuristic algorithms are used widely in order to solve optimization problems [2]. For example, we can mention the following: Particle Swarm Optimization (PSO) which is based on the social behavior of birds [3], Ant Colony Optimization (ACO) which draws inspiration from the behavior of ants to find the food [4], Honey Bee Mating Optimization Algorithm (HBMO) which is based on the mating process of the honey bees [5,6], genetic algorithm (GA) that is based on natural evolution, such as inheritance, mutation, selection, and crossover [7]. Differential Evolution based on especial the crossover and selection operators similar to GA [8], artificial bee colony (ABC) algorithm which is based on the intelligent foraging behavior of honey bee swarm [9], Harmony Search (HS) which is inspired by the music player improvement [10, 11], etc.. Although these algorithms could solve many nonlinear optimization problems but there are still some limitation in their performance such as trapping in local optima, dependability on initial parameters, etc.. This study will investigate some of these problems below. In PSO it is important to adjust initial weight matrix and learning rate well [3, 12], dependability on the mating process is the problem which HBMO encounters with [5], Differential Evolution algorithm depends on differential weight, crossover probability and population size [8, 13].

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This paper has chosen shuffled frog leaping algorithm (SFLA) to optimize nonlinear multi-objective problems. We have applied a new modification on SFLA in two phases in order to find better solutions. SFLA is a swarm based optimization algorithm witch is based on natural memetics. It is preferred to other evolutionary algorithms such as PSO and GA due to its computational time and global search ability [14, 15]. SFLA contains a set of frogs. These frogs are divided in to different subsets called memplexes. In each memplex there are some frogs with different cultures, and perform a local search and each frog can effect on the idea of the other frogs through a memetic evolution process. Moreover the ideas can be exchanged among memplexes via a shuffling process. Consequently, the algorithm contains both local search and global exploration. The modifications which we have proposed will improve the SFLA performance for local and global search [16]. The remainder of this paper is organized as follows: section 2 describes shuffled frog leaping algorithm and its modifications, section 3 discusses experimental results and finally section 4 presents research conclusion.

2. Shuffled Frog Leaping Algorithm

2.1. Original SFLA

The SFLA is a memetic metaheuristic algorithm which is based on swarm intelligence. Each frog is composed of memes $X_i=[X_{i,1}, X_{i,2}, \ldots, X_{i,n}]$. Consider k frogs in the population which are divided to m_x memplexes, each including n_k frogs ($k = m_x * n_k$). Afterwards the algorithm will sort all of the frogs according to the fitness function. The formation of the memplexes is in this way that the first frog goes to the first memplex, the second frog goes to the second memplex, the mth frog goes to mth memplex and the m+1th frog returns to the first memplex. The best and the worst frogs in the jth memplex are defined as $X_{b,j}$ and $X_{w,j}$ respectively. Then applying an evolution process in each memplex, the position of the worst frog (X_w) is improved as follows:

$$D_x = rand().(X_b - X_w) \qquad (1)$$
$$X_w^{new} = X_w^{old} + D_x$$

Rand is a random value in the range [0,1]. If this process can improve the position of X_w, then it replaces X_w, otherwise the above equation is repeated with X_g (the frog with global best fitness) instead of X_b. If again, no improvement occurs, then a new random frog is generated and X_w will be replaced. It is repeated for a defined number of iterations. Then the memplexes are reshuffled and X_g is updated. The process is continued until the termination criteria are achieved [14, 17]. Although SFLA has many advantages such as high robustness, simple idea, etc. nevertheless it may suffer premature convergence [16, 18], hence we suggest a modification for this algorithm in two phases which is discussed in the following section. This modification will also improve the search ability of SFLA.

2.2. Modified SFLA

As mentioned before, SFLA is a powerful optimization algorithm that has shown superior performance than a number of evolutionary algorithm BA [19], KH [20-21], CSA [22-24], HS [25], FA [26-27], TLBO [28-29], CA [30], HBMO [31-32]. Nevertheless, we propose a new modification method to improve the total search ability of SFLA greatly. This modification method is applied to SFLA in order to increase the total search ability of the SFLA and to avoid the premature convergence. In the first phase we use a random walk to increase the diversity of the population. It is called Lévy flight. In this random walk step-lengths are distributed according to a heavy-tailed probability distribution. It can be expressed as the following formulations:

$$Le'vy(\omega) \sim \tau = t^{-\omega} \quad ; \quad (1 < \omega \leq 3) \tag{2}$$

$$X_i^{new} = X_i^{old} + \varphi_1 \oplus Le'vy(\omega) \tag{3}$$

Where t is the iteration number and φ_1 is a random value in the range [0,1]. If the new solution is better than the last one then the process replaces it. Now in the second phase of the modification we intend to move the average of the population toward the best solution. Consequently the mean value of the population column-wise M_p should be computed, then each solution in the population is updated as follows:

$$X_i^{new} = X_i^{old} + T_F(X_{Gbest} - X_i^{old}) \tag{4}$$

X_{Gbest} is the best frog in the population and T_F is a random integer equal to 1 or 2.

3. Experimental results and discussion

This study used several benchmarks which supplies different features such as separability and multimodality. Separability means the differentiability characteristics of a function in the search space; multimodality means a function with several local optimal. Optimizing a non-separable function is difficult and if it is multimodal too, the difficulty becomes more. In this section we will use different functions in order to evaluate the performance of the suggested algorithm.

3.1. First experiment design

First we use five different benchmarks as the test functions [33]. Tables 1 and 2 show the detailed data of the benchmarks. We compare algorithms with each other with two metrics: the success Percentage (SP) and the Average Function Evaluations (AFE). SP identifies how much the proposed algorithm is stable in order to find the optimal solution and AFE shows how much computational effort it needs to find the optimal solution. This research considers the fittest solution achieved by the algorithm and the global optimum solution in order to determine the algorithm's success; if the difference between them becomes less than 0.001 of the global optimum, the algorithm is successful [33]. In our experiment population size is considered to be twenty, but there is an exception for the Rosenbrock function, we assume population size to be fifty for this function, also we have run the simulation for one hundred times. Table 2 depicts the MSFLA results for SP which is similar to the other algorithms but the results for AFE are better comparing to the others.

TABLE 1: DETAILED DATA OF THE BENCHMARKS CONSIDERED IN EXPERIMENT 1 [33]

Bench. no	Function	Range	Global optimum
1	De Jong	[-2.048,2.048]	F_{min} = 3905.93, X = (1,1)
2	Goldstein and Price	[-2, 2]	F_{min} = 3, X = (1,1)
3	Martin and Gaddy	[0,10]	F_{min} = 0, X = (5, 5)
4 (a)	Rosenbrock (D = 1)	(a) [-1.2, 1.2]	F_{min} = 0, X = (1, 1)
4 (b)		(b) [-10,10]	F_{min} = 0, X = (1, 1)
5	Rosenbrock (D = 3)	[-1.2, 1.2]	F_{min} = 0, X = (1, 1, 1, 1)
6	Hyper Sphere (D = 6)	[-5.12, 5.12]	F_{min} = 0, X = (0, 0, 0, 0, 0,0)

TABLE 2: THE VALUES OF SP% & AFE FOR GA, ABC, GRENADE EXPLOSION METHOD (GEM) AND MSFLA

Bench. no	GA		ABC		GEM		Proposed algorithm (MSFLA)	
	Suc %	AFE	Suc %	AFE	Suc %	AFE	Suc %	AFE
1	100	10160	100	868	100	746	100	704
2	100	5662	100	999	100	701	100	660
3	100	2488	100	526	100	258	100	240
4 (a)	100	10212	100	631	100	572	100	545
4 (b)	-	-	100	2306	100	2289	100	1123
5	-	-	100	28529	100	82188	100	2611
6	100	15468	100	7113	100	423	100	332

3.2. Second experiment design

In this experiment we use a benchmark consisted of six objective functions [34]. Table 3 shows the detailed information of the objective functions. As can be seen in table 4, the performance of the proposed algorithm has been compared to some other algorithms. The number of simulation run was two hundred times and the population size is considered to be twenty. In this experiment we have assumed another criterion called Error which denotes the average difference between the global optimum and the obtained best solution. As the results show the suggested algorithm has good consistency with SP=100% for all the benchmarks. Hence regarding to the SP, AFE and Error values, the excellence of our method is demonstrated.

TABLE 3: DETAILED DATA OF THE BENCHMARKS CONSIDERED IN EXPERIMENT 2 [34]

Bench. no	Function	Range	Global optimum
1	Powell badly scaled	[-50, 50]	F_{min} = 0, X = (1.098 e5, 9.106)
2	B2 function	[-50, 50]	F_{min} = 0, X = (0,0)
3	Booth function	[-50, 50]	F_{min} = 0, X = (1, 3)
4	Griewank (D = 10)	[-50, 50]	F_{min} = 0, X = (0,0, …)
5	Rastrigin (D = 10)	[-50, 50]	F_{min} = 0, X = (0, 0)
6	Sphere (D = 30)	[-50, 50]	F_{min} = 0, X = (0, 0, …)
7	Griewank (D = 50)	[-50, 50]	F_{min} = 0, X = (0, 0, …)

TABLE 4: THE VALUES OF SP%, AFE & ERROR FOR PSO, ACO AND MSFLA

Bench. no	PSO		ACO		Proposed (MSFLA)	
	Suc %	AFE	Suc %	AFE	Suc %	AFE
1	94	20242	100	2971	100	2920
2	100	4188	100	1124	100	1087
3	100	3848	100	1065	100	901
4	0	504657	82	14076	100	1125
5	30	510050	60	12353	100	2131
6	0	4530150	100	87004	100	3312
7	0	2550250	82	378354	100	2123

3.3. Third experiment design

In this experiment we have used five benchmarks. Table 5 represents the detailed data of the benchmark problems [21]. The metrics which we have considered in this experiment are mean and standard deviation (SD). The average ability of the algorithm in order to find the global solution is determined by mean. SD specifies variation from the mean value. This experiment compares the proposed algorithm with HS, Improved Bee Colony (IBC) and ACO. The number of times of objective function evaluation affects on the number of runs of the algorithm, therefore it is worth noting that the maximum number of function evaluations for ACO, HS and IBC is 50000 [35] and for SFLA is 15000. Table 6 shows the performance of the algorithms considering the dimensionality of the benchmarks.

TABLE 5: DETAILED DATA OF THE BENCHMARKS CONSIDERED IN EXPERIMENT 3 [35]

Bench. no	Function	Range	Global optimum
1	Sphere	[-100, 100]	F_{min} = 0, X = (0, 0, …)
2	Rosenbrock	[-30, 30]	F_{min} = 0, X = (1,1, …)
3	Rastrigin	[-5.12, 5.12]	F_{min} = 0, X = (0, 0, …)
4	Griewank	[-600, 600]	F_{min} = 0, X = (0,0, …)
5	Ackley	[-32, 32]	F_{min} = 0, X = (0, 0, …)

TABLE 6: THE VALUES OF MEAN & SD FOR HS, ACO, IBC AND MSFLA

No	D	HS		IBC		Proposed MSFLA	
		Mean	SD	Mean	SD	Mean	SD
1	5	3.20 e-10	2.89 e-10	4.30 e-17	1.07 e-17	3.87 e-27	6.32 e-28
	30	7.21 e+00	3.62 e+00	4.69 e-16	1.07 e-16	5.53 e-18	4.11 e-25
	50	5.46 e+02	9.27 e+01	1.19 e-15	4.68 e-16	1.23 e-20	5.90 e-22
	100	1.90 e+04	1.78 e+03	1.99 e-06	2.26 e-06	4.21 e-20	7.77 e-21
2	5	5.94 e+00	6.71 e+00	2.33 e-01	2.24 e-01	2.21 e-01	3.39 e-02
	30	3.82 e+02	5.29 e+02	9.98 e-01	1.52 e+00	2.56 e+01	1.32 e+00
	50	2.47 e+04	1.02 e+04	4.33 e+00	5.48 e+00	4.53 e+01	3.44 e+00
	100	1.45 e+07	2.16 e+06	1.12 e+02	6.92 e+01	8.56 e+01	9.76 e-01
3	5	6.07 e-08	5.52 e-08	4.34 e-17	110 e-17	0.00 e+00	0.00 e+00
	30	7.40 e-01	7.00 e-01	4.80 e-05	243 e-04	0.00 e+00	0.00 e+00
	50	3.76 e+01	4.87 e+00	4.72 e-01	4.92 e-01	0.00 e+00	0.00 e+00
	100	3.15 e+02	2.33 e+01	1.46 e+01	4.18 e+00	0.00 e+00	0.00 e+00
4	5	2.60 e-02	1.38 e-02	4.04 e-17	1.12 e-17	9.64 e-16	7.22 e-28
	30	1.09 e+00	3.92 e-02	5.82 e-06	3.13 e-05	2.05 e-14	6.32 e-26
	50	5.81 e+00	9.16 e-01	5.72 e-01	9.22 e-01	7.21 e-11	3.65 e-25
	100	1.78 e+02	1.98 e+01	1.31 e+01	6.30 e+00	3.21 e-10	6.43 e-25
5	5	2.68 e-05	1.24 e-05	9.64 e-17	5.24 e-17	0.00 e+00	0.00 e+00
	30	9.43 e-01	5.63 e-01	3.86 e-15	3.16 e-15	1.23 e-20	1.72 e-13
	50	5.28 e+00	4.03 e-01	4.38 e-08	4.65 e-08	6.72 e-10	1.86 e-13
	100	1.32 e+01	4.90 e-01	1.32 e-02	1.30 e-02	1.31 e-12	1.54 e-13

As can be seen in table 6, the superiority of the suggested method is apparent in terms of mean and SD. The consistency of the proposed algorithm can be inferred because increasing the dimension of the benchmark can cause changes in MSFLA a little. Additionally this study has improved the SFLA by adding two modification phases; therefore the total search ability of the SFLA has increased as well as it can avoid the premature convergence. Thus this paper could introduce a modified algorithm to handle complex nonlinear large-scale optimization problems. The effectiveness and the ability of the proposed algorithm in finding the global optimal solutions are demonstrated through simulations which have been done on several benchmarks.

4. Conclusion

Complex nonlinear multiobjective optimization problems have some characteristics which cause conventional methods can not solve them properly. Further more there are some evolutionary algorithms such as GA, PSO, HS, HBMO, etc. which are dependent to their initial parameters in order to perform well. Hence this study proposed an algorithm that although has some similarities to other swarm based algorithms but it has simple idea and high robustness. Further more with a two-phase modification the proposed algorithm would work better in terms of search ability and avoiding premature convergence.

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