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CGBDE - Presentation of a New Combined Method for Optimization

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ABSTRACT

This paper presents a new combined method for optimization of functions called CGBDA. The method is formed by combining optimization algorithm of theCooperative Gases Brownian Motion Optimization and the great deluge algorithm (GDA). Local search property of GDA is used for algorithm accuracy and the result thereof is given to the Cooperative Gases Brownian Motion Optimization to improve search power. Performance of the proposed method is shown through implementing it on some problems of criterion and efficiency of the method is evaluated by comparing the obtained results with the available ones through another method such as GeneticAlgorithm(GA),the Particle Swarm Optimization(PSO)algorithm, Imperialist Competitive Algorithm (ICA) and the gases Brownian motion.

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INTRODUCTION

Evolvable algorithms are the methods based on random search, which were modeled by natural biological evolutionary modeling. They work on some possible responses that enjoy superior characteristics with further survival of generation; therefore, they provide a closer estimationofthe optimal response. In each generation, a new set of estimations is produced based on selecting members with further fitness and they combine similar to what happens in nature. Consequently, this process encompasses evolution of the individuals who are more compatible with their parents in an environment, exactly similar to what happens in nature. Evolvable algorithms model natural processes, such as selection, combination (recombination), mutation, migration, place or position, and adjacency. Evolvable algorithms work on populations of individuals instead of a single-response; therefore, search can be done in a parallel manner. At the beginning, some individuals of a society are guessed randomly. A target function is calculated for each individual. The first generation is created. In case none of the termination criteria for optimization appears, creation of the next generation will be started. The individuals are selected according to their competence for producing offspring. The individuals are considered as parents and produce offspring using recombination. All the offspring are then changed genetically with a certain amount of probability, i.e. the same mutation. Now, competence (fitness) of the offspring is determined, they replace with the parents in the society, and create the new generation. This cycle is repeated as long as one of the criteria of the termination criteria for optimization is gained. The algorithm will be like this. If a single-society evolution is robust enough, it can be efficient in a wide range of issues. However, better results will be obtained by creating several sub-societies. Each sub-society is formed on several separated generations (such as a single-society evolutionary algorithm) and no member will be displaced among the sub-societies prior to it. A multi-society evolutionary algorithm models evolution of species in proportion to a single society evolutionary algorithm using a method more similar to nature.The above discussion proves that evolutionary algorithms are basically different from other optimization methods and old conventional search. Some of the differences are as follows:

- Evolvable algorithms do not search merely a single point, but a population of points in a parallel manner
- Evolvable algorithms do not need tacit information or other complementary knowledge.
- Objective function and related competence are effective in search directions.
- Evolvable algorithms enjoy the rules, which are likely to change, not certain and specified items.
- Evolvable algorithms provide many acceptable responses and a user is responsible for making the final choice.

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Therefore, where the relevant problem does not include a single response, for instance a family of optimal-pareto responses, similar to what is in a multi-objective optimization and timetabling problems, revolutionary algorithms are inherently effective for identifying such multiple responses at the same time. In recent years, evolutionary algorithms refer to all the modern and high-level algorithms, including GA, simulated annealing(SA) algorithm, tabusearch (TS), ant colony (AC) algorithm [1], PSO [2], bees algorithm (BA) [3], harmony search (HS) algorithm [4], firefly algorithm (FA) [5]and GBMO algorithm [15]. This algorithm proposes a method for searching the space of optimization problems using Browniannatureofmotion of gas molecules,which enables them to move across quickly in the space they are,dissipate all over the space, and model their kinetic motion.

Other type ofsimulated annealing algorithms, which is very similar to simulated annealingtechnique, is deluge algorithm. By defining a parameter called *water level*, anareais determined in this algorithm to obtain responses and the response is compared with this parameter each time. This algorithm was applied in [6] well for solving peddler 442 and 532 problem. Drive *et al.* presented a type of modified linear deluge algorithm in [7] for solving tests timetabling problem. Burke used this algorithm for solving tests timetabling problem in [8,9]. Khatab*et al*. applied the algorithm for optimizing efficiency of series-parallel systems in [10]. Nahas*et al*. used the algorithm for solving Bagher allocation problem in unreliable production lines. The algorithm's efficiency on dynamic layout problem was measured by improving deluge algorithm. Finally, deluge combined method with ant colony was used for solving redundancy allocation problem [13]. Another method discussed here is GBMO algorithm. This algorithm is an optimization method, which is inspired by motion of gas molecules. Simplicity, implementation, scalability in dimensions and appropriate experimental efficiency are among its favorable characteristics. In addition to proposing a new model by combining GBMO algorithm and deluge algorithm, which appropriately used both local and general properties of the above algorithms, a version of Cooperative Gases Brownian Motion Optimization algorithm was also provided that could relatively improve the results obtain from the different sets of this algorithm.

GMBO Algorithm:

Molecular motion in gas has a Brownian nature. There is no superior direction for molecular speed in gases and they are distributed in all directions erratically. Direction and speed of molecules are constantly changed due to contact of molecules. Therefore, speed of gas molecules is considerably different. Browning nature in gas molecules motion enables them to move across the space they are and occupy all the volume of the place in which they are diffused.

Inspiring Brownian motion nature in gases, a method was considered in the proposed GBMO algorithm for searching optimization problems space whose efficiency in searching problem space using the earlier optimization methods is considerable.

Step 1: A set of gas molecules is randomly formed in a search space.

Step 2: A radius is considered randomly in [0,1] interval for each molecule.

Step 2: System temperature, which is a parameter to guarantee an algorithm's convergence, is initiated.

Temperature is high at the beginning of a search and it lowers over time. At first, search process searches a wider area (general search) due to high amount of kinetic energy.With the increase of speed of molecules, it searches a wider area (general search). With the temperature lowering, which leads to reduction of the kinetic energy and the speed of molecules motion, they will mainly have local search over time.

Step 3: Speed and place of molecules are calculated and updated as per the following formulas.

$$v_t = v_{t-1} + \sqrt{\frac{3KT}{m}} \quad (1)$$

$$x_t = x_{t-1} + v_t \quad (2)$$

Step 4: Fitness function is called to evaluate the obtained responses. The best responses are kept to compare with the obtained results.

Step 5: In addition to moving in different directions, each molecule vibrates in its own place and a specified radius.The vibration generates a further local search at first and a more general search at final steps.

$$\theta_{n+1} = \theta_n + b - \left({}^{a}/_{2\pi}\right)\sin(2\pi\theta_n)\, mod(1) \quad (3)$$

Molecules vibration was modeled using a chaotic sequence generator. In the above formula, a=0.5 and b=0.2, which shows place of motion of each molecule. Figure 1 shows the diagram of vibrationalmotion of molecules in gases. This vibration is different for various molecules and it is within the defined radius.

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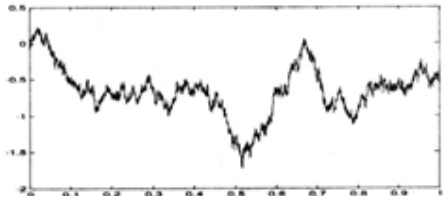

Fig. 1: Molecular vibrational motion with radius one.

Step 6: Fitness function is called to evaluate the obtained responses. The best responses are kept to compare with the obtained results.
Step 7: Algorithm Termination Condition: Temperature is controlled. If it reached zero, the algorithm would be terminated; otherwise, search would be continued.

This algorithm implements general and local search ability with random and vibrational motions of molecules in a space. Figure 2 shows the motions.

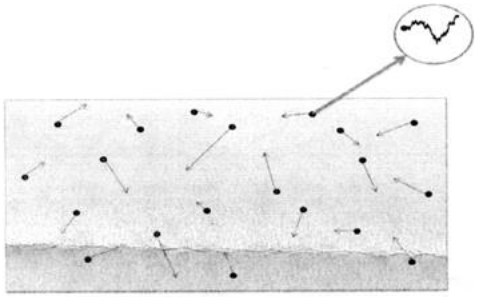

Fig. 2: Random and vibrational motion of molecules in problem's search space.

Figure 2 shows that gas molecules of each move in random direction irregularly and search in their own placevibrationally.Figure 3 shows flowchart of the proposed algorithm.

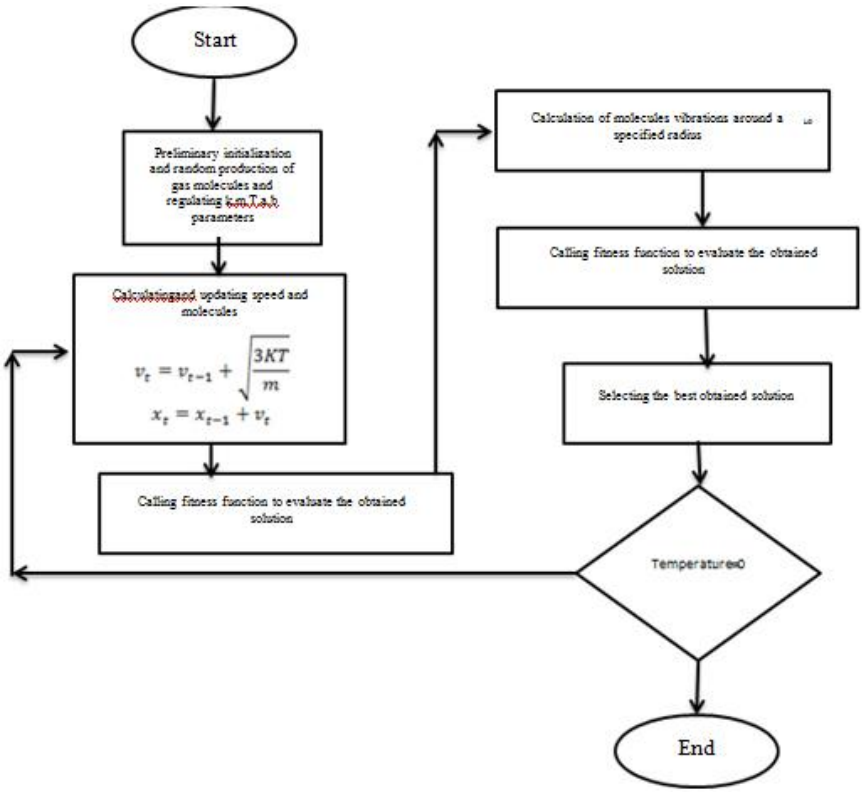

Fig. 3: GBMO Algorithm Flowchart.

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Deluge Algorithm:

Deluge algorithm is one of the optimization problems proposed by Dueck in 1993. This method selects new solutions from adjacency of the earlier responses and replaces common solutions with the best responses in case they are better. For minimization problems, the responses will be selected whose values are smaller or equal to water level (WL) and the initial WL will be equal to the initial response. In dilute algorithm, WL value reduces evenly in each step and lowers as a certain amount. The reduction is continued as long as no response is found, which is better than the best ones found so far and WL is equal to the best response found so far. Of course, the algorithms is also iterated several times in this step so that it terminates if no better result is found.Figure (4) shows pseudo code of the algorithm.

```
Choose an initial configuration as Old_Config
Choose WL and Up
For n=۰ to # of iterations
Generate a small stochastic perturbation…
New_Config of the solution
If Fitness (New_Config) > WL
Old_Config := New_Config
End If
WL = WL + DOWN
End For
```

Fig. 4: Pseudo code of deluge algorithm.

Proposed Algorithm:

Here, a combination of local and general characteristics of GBMO algorithm and deluge algorithm is used, a method is proposed, and the model is used in the Cooperative Gases Brownian Motion Optimization.

GBDE Algorithm:

A combination of GMBO algorithm and deluge algorithm is used in the proposed algorithm. By combining the global characteristic of GMBO and local characteristic, deluge algorithm is used appropriately. First, an optimal response is searched through GMBO for searching with the steps longer than the ones of deluge algorithm. After finishing the algorithm and obtaining the results, values of the results are considered as input data for deluge algorithm. In this stage, the algorithm conducts a search in the provided space with much smaller steps.

CGBDE Algorithm:

Cooperation characteristic was first applied by potter [16] on GA to solve optimization problems. This idea was later used considerably by researchers and it was applied on PSO algorithm by Van den Bergh [17]. In the newly presented algorithm (CGBDE), a mass (population) of gases is allocated to each dimension of problem space. In fact, N swarm of one-dimensional gas molecules is used instead of using N-dimension gas molecules in a swarm. Each population of gas molecules is responsible for optimization of a dimension and they cooperate to optimize an N-dimension vector, in a way that the best particle in each group is selected and considered as the representative of that dimension. Therefore, values of the best particles in each N group is introduced as the major N-dimension vector and only values of the same dimension of the N-dimension vector is changed in each iteration of the algorithm for gas molecules of group a.This way, to calculate value of gas molecule in a^{th} dimension, its value is put in the main vector and its size is calculated. Performance of the proposed method is shown through its implementation on some problems of criterion and efficiency of the method is also evaluated through comparing the results with the ones in other articles.

Simulation Results and Comparison of them with other Algorithms:

To evaluate performance and study convergence rate and solution quality, the proposed algorithm (CGBDE) was executed on five standard functionsthat include simulation of some of N-variable functions usually applied most as standard functions for measuring optimization algorithms. Results of the above algorithm are compared with standard PSO, GA, ICA, and GBMO algorithms. The functions that are often used in evolutionary methods are 1) ROSENBROCK, 2) SPHERE, 3) RASTRIGIN, 4) ACKLEY, and 5) STEP, which are defined in Table (1).

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Table 1: Standard functions of ROSENBROCK, SPHERE, RASTRIGIN, ACKLEY, and STEP.

Name of Function	Function Equation
ROSENBROCK	
SPHERE	
RASTRIGIN	
ACKLEY	

In order to make the results of this algorithm comparable with the algorithms available in the articles, all the functions were tested separately with 10, 20, and 30 dimensions. Each function was executed 20 times and the mean value of the optimal solution was obtained. Table 2 shows the parameters that should be regulated in GBMO, GBDE, ICA, PSO, and GA algorithms and their values. Sogno function, as inertia weight decline curve, was used in the PSO algorithm to compare the results. [14]

Table 2: Parameters of GBMO, PSO, GA, ICA algorithms.

Parameters	Algorithms
Num of countries=80,num of initiallmperilists=8,num of decades=1=000,revolutionrate=0.3,assimilation coefficient=2,zeta=0.02	ICA
POPSIZE=80,MAXgeneration=1000,crosspercent=50/100,mutationrate=0.02,selection mode,tournament	GA
C1 = 1.5, C2 = 1.5, G=HIJKAHIJKLMN,S=-0.5, ParticleSize = 80, MaxIter = 1000	PSO
MoleculeSize = 80, Temperature = 100, a=0.5 _b=0.2	GBMO

Table 3: Mean of optimal value for 20 times execution of the functions in 10 dimensions.

CGBDE	GBMO	ICA	PSO	GA	
3.76e-22	4e-9	6.2799e-11	1.1405e-17	0.2499	F1
8.1817e-18	7.9357e-9	0	0	1.0993e-11	F2
9.649e-17	8.0096	0.4466	0.0020	48.9673	F3
2.55e-21	1.7e-11	1.9386e-7	0.0298	0.1016	F4

Table 4: Mean of optimal value for 20 times execution of function in 20 dimensions.

CGBDE	GBMO	ICA	PSO	GA	
3.4e-25	8e-9	0.0732	0.0143	3.2958	F1
1.3829e-21	1.5871e-8	8.4028e-4	5.4021e-4	0.6609	F2
2.14e-19	18.3735	1.9191e3	19.5173	1.3182e3	F3
5.49e-27	2.5602e-5	0.1205	0.2105	2.1664	F4

Table 5: Mean of optimal value for 20 times execution of function in 30 dimensions.

CGBDE	GBMO	ICA	PSO	GA	
8.88e-26	1.2e-8	28.7678	9.0371	18.8398	F1
4.076e-23	2.3807e-8	0.4128	0.0015	6.3023	F2
2.4108 e-19	28.0826	1.0179e6	28.7533	9.8512e3	F3
9.6024e-22	2.5602e-5	19.9587	1.0289	3.0695	F4

As the above table show, performance of the proposed algorithms is better than the one of other known algorithms, which is due to the application of deluge algorithm and its cooperative approach.

Conclusion:

This paper proposed a new model for optimization based on the Cooperative Gases Brownian Motion Optimization and GDA models. This algorithm, which is called CGBDA, uses local characteristic of deluge algorithm with very small steps for searching space more accurately and the Cooperative Gases Brownian Motion Optimization. CGBDA algorithm was applied on 5 functions, its results were compared with the ones obtained from execution of PSO, ICA, GA, GBMO algorithms, which shows better performance and higher speed in terms of its percentage of success to find optimal performance.

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