Adaptive Weight Gradient Based Optimization

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Abstract

This paper proposes an improved gradient based optimizer (GBO) that combines an adaptive weight factor mechanism, named WGBO, to tackle the parameter identification problem in classical engineer optimization problems. the comparison results reveal that it is feasible to find a better solution using the pro-posed WGBO to the same problem compared to the existing methods.

Keywords

Gradient Based Optimizer; Adaptive Weight Mechanism; Classical Engineer Optimization Problems.

1. Introduction

With the increasing complexity and dimensionality of data, all information of feature space is unknown in various fields such as machine learning and industrial de-sign, so it is impossible to consider the accurate mathematical model to solve all problems as the best solution [1]. Therefore, in the past decade, swarm intelligence algorithms have become the research focus of different optimization problems [2]. Com-pared to traditional optimization algorithms [3], Meta-heuristics algorithm initially solve the space at the beginning, and this randomness allows the search agents to be widely distributed throughout the search space, which is a good way to avoid the algorithm falling into local optimality [4]. Based on the above considerations, the Me-ta-Heuristic Algorithm is particularly suitable for solving practical problems in the real world where the search space is unknown. On the other hand, according to the no Free Lunch Theorem (NFL) [5], no single algorithm can be applied to all optimization problems and find the best answer for all problems. In other words, one algorithm may obtain good results on some problems, but poor results on others (because the nature of the problem is different).

The pseudo-code execution process of WGBO is shown in Table.1. and the flowchart of WGBO is shown in Fig.1. In conclusion, this paper mainly completes the following works. An improved GBO with adaptive weight mechanism is named WGBO, which is tested in 30 IEEE CEC 2014 test functions. The IEEE CEC 2014 test functions include unimodal functions, multimodal functions and composite functions, is used to verify the capability of the proposed WGBO. The proposed algorithm WGBO is compared with conventional and advanced algorithm to evaluate the performance. And it is applied in Press vessel design problem. The effectiveness of WGBO is verified by describing and analyzing the classic practical problem in detail.

Table 1. Pseudo-code of WGBO

Algorithm: WGBO
Step 1. Initialization
1). Assign the initial parameters ε, m, *FES*, *MaxIt*, *nP*, *nV*;
2). Generate the initial population $X_0 = [x_{0,1}, x_{0,2}, \dots, x_{0,D}]$;
3). Evaluate the objective function value $f(x_0), n = 1,2, \dots, N$;
4). Specify the best and worst solution x^m_{best}, x^m_{worst};
5). *FES*=*FES*+*N*;

Step 2. Main loop.

6). While *FES*≤*MaxIt*

7). Set the parameter of α , β and pr;

8). for *i*=1:*nP*

pr=*FES/MaxIt;*

Gradient search rule (GSR)

9). Select randomly r_1, r_2, r_3 and r_4 in the range of [1, *nP*];

10). Obtained the value of *DM* and *GSR*;

11). if *rand* <pr;

Local escaping operator (LEO)

12). Further calculate the position x_n^{m+1} by Eqs. (18)-(24)

13). end if

14). Evaluate the position x_n^{m+1};

15). Update the position x_{best}^m and x_{worst}^m;

16). *FES*=*FES*+1;

17). end for

18). *m*=*m*+1

19). end while

Step 3. Return x_{best}^m

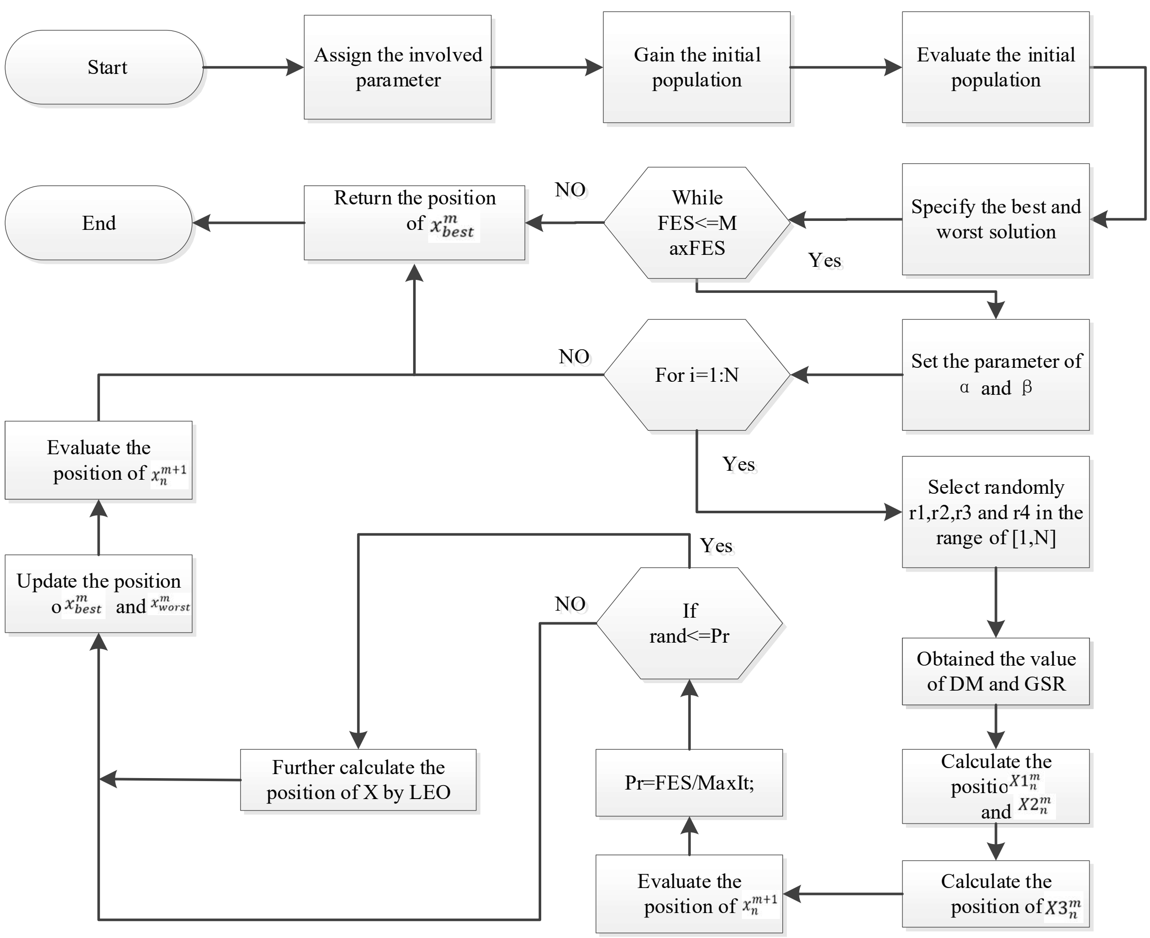

Fig. 1 The flowchart of WGBO

2. Press vessel design problem

The mathematical model aim to minimize the total cost of cylindrical PV, which is closely related to material, structure, and welding. The end of the PV is covered, and the front has a hemispherical figure. In PVD problem, the thickness of the shell (T_s) and head (T_h), inner radius (r) and the range of cross-section minus head (l) are all variants which should be optimized. The method are described as follows.

Consider $\vec{x} = [x_1\ x_2\ x_3\ \ x_4] = [T_s\ T_h\ R\ L]$

Objective: $f(\vec{x})_{min} = 0.6224x_1x_3x_4 + 1.7781x_3x_1^2 + 3.1661x_4x_1^2 + 19.84x_3x_1^2$

Subject to $g_1(\vec{x}) = -x_1 + 0.0193x_3 \leq 0,$

$$g_2(\vec{x}) = -x_3 + 0.00954x_3 \leq 0,$$

$$g_3(\vec{x}) = -\pi x_4x_3^2 - \frac{4}{3}\pi x_3^3 + 1296000 \leq 0,$$

$$g_4(\vec{x}) = x_4 - 240 \leq 0,$$

Variable ranges:

$$0 \leq x_1 \leq 99,$$

$$0 \leq x_2 \leq 99,$$

$$10 \leq x_3 \leq 200,$$

$$10 \leq x_4 \leq 200.$$

Many meta-heuristic methods have tried this mathematical model. He et al. [6] proposed PSO to solve this problem. The optimal cost was 6061.0777. Deb et al. [7] use GA to try this optimization problem. The optimal cost of 6410.3811 is realized. At the same time, ES [8], IHS [9], Lagrangian multiplier [10], Branch-and-bound and many mathematical methods are all used to handle this task.

When calculating the pressure design problems, the optimization results of the algorithms in the literature are shown in Table 2. It can be seen from Table 8, the minimum value of WGBO is 6003.595, that is, when TS, Th, R and L are set to1.06906, 0.545644, 55.11479, and 66.15956 respectively, the total cost of cylindrical PV is the minimum. Among these algorithms, WGBO can obtain the best feasible optimization design. Therefore, WGBO can provide powerful help for PVD problem.

Table 2. Results of WGBO versus peers in literature for PVD case

Algorithm	Optimum variables				Optimum cost
	T_s	T_h	R	L	
WGBO	1.06906	0.545644	55.11479	66.15956	6003.595
IHS	1.125000	0.625000	58.29015	43.69268	7197.7300
PSO	0.812500	0.437500	42.091266	176.746500	6061.0777
GA	0.937500	0.500000	48.329000	112.679000	6410.3811
ES	0.812500	0.437500	42.098087	176.640518	6059.7456
Lagrangian multiplier	1.125000	0.625000	58.291000	43.690000	7198.0428
Branch-and-bound	1.125000	0.625000	47.700000	117.71000	8129.1036

3. Conclusion

The research and application of GBO are in its infancy, So there are still many problems of GBO to be further studied. Firstly, the traditional meta-heuristic algorithm can be combined with GBO, balancing the global and local search capabilities better and improving the overall optimization potential of GBO. Secondly, how to apply WGBO to solve multi-objective problems and dynamic windows for other related topics which need a very competitive optimizer. The proposed WGBO approach is not only an efficient tool for to the classical engineering problems, but also utilized and evaluated its performance for recognizing the feasible solutions to the deep learning scenarios, image processing, feature selection, information fusion, modelling and study of wireless sensor networks

(WSNs), multipath routing, WSN-assisted opportunistic networks, and water pollution prediction, disease diagnosis and social evolution modelling. In the future, there are still some researches that need to be done.

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