A New Improved Optimization Algorithm

Zhiqing Chen

Department of electrical and Electronic Engineering, Wenzhou Polytechnic, Wenzhou 325035, China.

Abstract

In this paper an improved gradient-based optimizer (GBO) which combines an adaptive weighting factor mechanism called WGBO is proposed. Comparing WGBO with GBO on CEC2014 test function, the results show that the proposed WGBO method can find a better solution. Further, WGBO is compared with the traditional algorithm on CEC2014 Functions, and the results show that WGBO performs very well.

Keywords

Gradient Based Optimizer; Adaptive Weight Mechanism; The Traditional Algorithm.

1. Component analysis

In this experiment, we used the test set from IEEE CEC 2014 test functions [1]. Where, the search range is [-100,100]. In order to ensure the fairness and control small error of the experimental results, these comparison algorithms are run independently for 30 times, and the population size is set to 30. The value of the maximum number of evaluations (MaxIt) is set to 300 000, and the dimension of the search space is set to 30. A detailed description of these test functions show in Table 1.

Table 1. Description of the CEC2014 benchmark functions

ID	Name of the function	Class	Optimum
CE01	Rotated High Conditioned Elliptic Function	Unimodal	100
CE02	Rotated Bent Cigar Function	Unimodal	200
CE03	Rotated Discus Function	Unimodal	300
CE04	Shifted and Rotated Rosenbrock's Function	Multimodal	400
CE05	Shifted and Rotated Ackley's Function	Multimodal	500
CE06	Shifted and Rotated Weierstrass Function	Multimodal	600
CE07	Shifted and Rotated Griewank's Function	Multimodal	700
CE08	Shifted Rastrigin's Function	Multimodal	800
CE09	Shifted and Rotated Rastrigin's Function	Multimodal	900
CE10	Shifted Schwefel's Function	Multimodal	1000
CE11	Shifted and Rotated Schwefel's Function	Multimodal	1100
CE12	Shifted and Rotated Katsuura Function	Multimodal	1200
CE13	Shifted and Rotated HappyCat Function	Multimodal	1300
CE14	Shifted and Rotated HGBat Function	Multimodal	1400
CE15	Shifted and Rotated Expanded Griewank's plus Rosenbrock's Function	Multimodal	1500
CE16	Shifted and Rotated Expanded Scaffer's F6 Function	Multimodal	1600
CE17	Hybrid Function 1 (N=3)	Hybrid	1700
CE18	Hybrid Function 2 (N=3)	Hybrid	1800
CE19	Hybrid Function 3 (N=4)	Hybrid	1900
CE20	Hybrid Function 4 (N=4)	Hybrid	2000
CE21	Hybrid Function 5 (N=5)	Hybrid	2100
CE22	Hybrid Function 6 (N=5)	Hybrid	2200
CE23	Composition Function 1 (N=5)	Composition	2300
CE24	Composition Function 2 (N=3)	Composition	2400
CE25	Composition Function 3 (N=3)	Composition	2500
CE26	Composition Function 4 (N=5)	Composition	2600
CE27	Composition Function 5 (N=5)	Composition	2700
CE28	Composition Function 6 (N=5)	Composition	2800
CE29	Composition Function 7 (N=3)	Composition	2900
CE30	Composition Function 8 (N=3)	Composition	3000

We can see the comparative results of WGBO and GBO that the adaptive weight mechanism can improve the ability of the algorithm to avoid falling into local optimum in multi-modal functions. According to the average ranking value (ARV) obtained by the IEEE CEC 2014 test functions, Also, Fig. 1 shows the convergence trend of different GBO variables on the IEEE CEC 2014 test functions. It can be seen that in F6, F8, F9, F10, F11, F13, F16, F22 and F30, the WGBO simultaneously achieves both faster convergence speed and higher solution accuracy than GBO in the test functions.

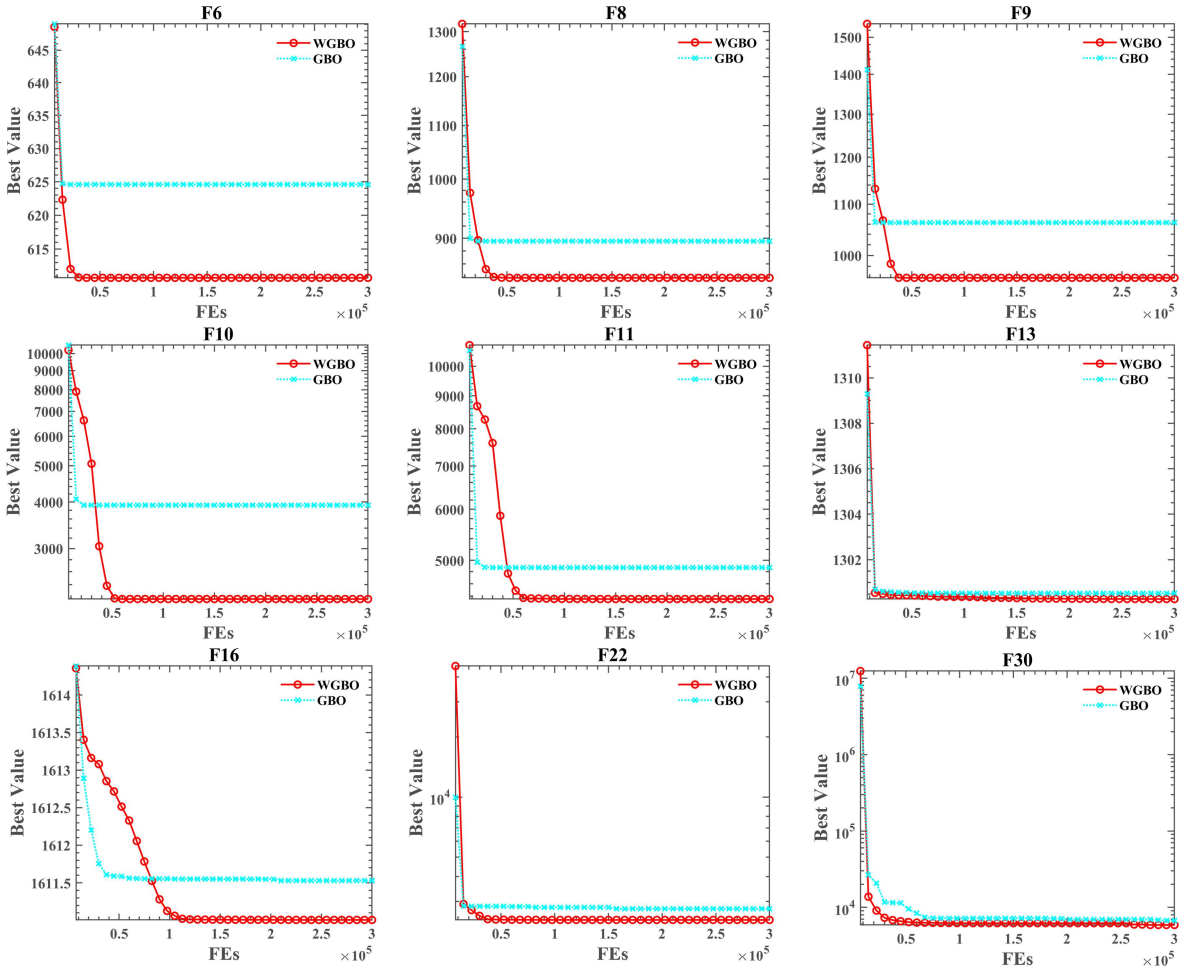

Fig. 1 The convergence trend of different GBO variables on the IEEE CEC 2014 test functions

2. Comparison of WGBO with conventional algorithms

In order to verify the effectiveness of WGBO, we compare WGBO with several mature original algorithms : GWO[2], MFO[3], BA[4], SCA[5], PSO[6] and WOA[7].

In the experiment, the number of function evaluations is set to 30,0000 and population size is set to 30 respectively, and the dimension of search space is set to 30. The comparison results are shown in Table 2. The mean and standard deviation of each algorithm executed 30 times independently on 30 functions are listed. Wilcoxon signed rank test [8] is also used to evaluate the advantages and disadvantages of WGBO compared with other original algorithms on 30 functions. As can be seen from the row of Table 3 "+/=/-", WGBO algorithm is significantly better than the other algorithms in most functions, and then we also use Friedman test [9] to sort all the algorithms involved. The ARV of WGBO is 1.27833, which is much lower than other algorithms. The results show that the proposed WGBO algorithm performs best among all the involved algorithms.

Table 2. Comparison of results for different algorithms

	F1		F2		F3	
	mean	STD	mean	STD	mean	STD
WGBO	**6.15E+04**	**3.33E+04**	**2.00E+02**	**4.79E-08**	**0.00E+00**	**2.15E-02**
GWO	6.74E+07	5.47E+07	3.01E+09	4.24E+09	5.40E-184	7.98E+03
MFO	4.43E+07	5.06E+07	1.37E+10	7.69E+09	2.13E+04	4.35E+04
BA	7.70E+05	3.48E+05	5.42E+05	3.92E+05	1.87E-01	8.51E+01
SCA	2.34E+08	9.43E+07	1.57E+10	2.61E+09	2.61E+01	5.17E+03
PSO	7.35E+06	2.04E+06	1.48E+08	1.59E+07	1.88E+02	1.92E+02
WOA	2.94E+07	1.17E+07	3.57E+06	5.54E+06	4.13E+01	3.23E+04
	F4		**F5**		**F6**	
	mean	STD	mean	STD	mean	STD
WGBO	**4.29E+02**	**3.60E+01**	**5.20E+02**	**1.35E-01**	**6.10E+02**	**1.93E+00**
GWO	6.49E+02	4.80E+01	5.21E+02	5.88E-02	6.14E+02	3.37E+00
MFO	1.62E+03	1.16E+03	5.20E+02	1.34E-01	6.24E+02	3.34E+00
BA	4.29E+02	3.57E+01	5.21E+02	6.10E-02	6.35E+02	2.58E+00
SCA	1.38E+03	2.85E+02	5.21E+02	3.76E-02	6.34E+02	2.52E+00
PSO	4.56E+02	2.93E+01	5.21E+02	5.05E-02	6.21E+02	2.72E+00
WOA	5.79E+02	5.48E+01	5.20E+02	1.28E-01	6.36E+02	3.18E+00
	F7		**F8**		**F9**	
	mean	STD	mean	STD	mean	STD
WGBO	**7.00E+02**	**1.75E-02**	**8.35E+02**	**7.74E+00**	**9.65E+02**	**1.44E+01**
GWO	7.26E+02	1.73E+01	8.72E+02	1.19E+01	1.01E+03	4.41E+01
MFO	8.31E+02	6.25E+01	9.43E+02	4.81E+01	1.12E+03	4.75E+01
BA	7.01E+02	2.07E-01	9.93E+02	3.02E+01	1.16E+03	5.56E+01
SCA	8.46E+02	3.31E+01	1.03E+03	1.51E+01	1.18E+03	1.90E+01
PSO	7.02E+02	1.49E-01	9.73E+02	1.96E+01	1.11E+03	2.05E+01
WOA	7.01E+02	5.27E-02	9.80E+02	3.13E+01	1.17E+03	6.56E+01
	F10		**F11**		**F12**	
	mean	STD	mean	STD	mean	STD
WGBO	**2.80E+03**	**5.75E+02**	**4.27E+03**	**5.72E+02**	**1.20E+03**	**2.77E-01**
GWO	2.99E+03	6.42E+02	4.24E+03	1.36E+03	1.20E+03	1.15E+00
MFO	4.12E+03	7.60E+02	5.45E+03	9.28E+02	1.20E+03	3.92E-01
BA	5.63E+03	1.01E+03	5.57E+03	5.83E+02	1.20E+03	3.01E-01
SCA	7.07E+03	7.92E+02	8.17E+03	2.71E+02	1.20E+03	2.85E-01
PSO	5.15E+03	5.88E+02	6.08E+03	6.73E+02	1.20E+03	3.47E-01
WOA	4.97E+03	6.86E+02	6.11E+03	1.24E+03	1.20E+03	6.08E-01
	F13		**F14**		**F15**	
	mean	STD	mean	STD	mean	STD
WGBO	**1.30E+03**	**9.62E-02**	**1.40E+03**	**1.80E-01**	**1.51E+03**	**2.08E+00**
GWO	1.30E+03	8.46E-02	1.40E+03	3.26E+00	1.65E+03	2.28E+02
MFO	1.30E+03	1.09E+00	1.45E+03	2.82E+01	4.21E+05	8.10E+05
BA	1.30E+03	9.16E-02	1.40E+03	4.96E-02	1.53E+03	5.81E+00
SCA	1.30E+03	2.40E-01	1.44E+03	4.52E+00	4.75E+03	4.15E+03
PSO	1.30E+03	7.84E-02	1.40E+03	1.26E-01	1.52E+03	1.47E+00
WOA	1.30E+03	1.07E-01	1.40E+03	3.39E-02	1.57E+03	3.09E+01
	F16		**F17**		**F18**	
	mean	STD	mean	STD	mean	STD
WGBO	**1.61E+03**	**7.74E-01**	**1.05E+04**	**5.22E+03**	**3.95E+03**	**1.80E+03**
GWO	1.61E+03	5.28E-01	1.10E+06	7.91E+05	7.16E+06	1.98E+07
MFO	1.61E+03	3.05E-01	6.37E+06	1.03E+07	3.95E+07	1.24E+08
BA	1.61E+03	3.34E-01	1.08E+05	6.92E+04	8.38E+04	2.03E+04
SCA	1.61E+03	1.91E-01	5.80E+06	2.05E+06	1.51E+08	1.09E+08

PSO	1.61E+03	4.16E-01	2.74E+05	1.58E+05	2.11E+06	6.19E+05
WOA	1.61E+03	3.94E-01	3.94E+06	1.97E+06	6.28E+03	4.81E+03
	F19		**F20**		**F21**	
	mean	**STD**	**mean**	**STD**	**mean**	**STD**
WGBO	**1.91E+03**	**2.12E+00**	**2.24E+03**	**1.00E+02**	**1.17E+04**	**6.03E+03**
GWO	1.93E+03	1.70E+01	1.50E+04	6.52E+03	9.29E+05	1.96E+06
MFO	1.96E+03	4.21E+01	4.74E+04	2.70E+04	6.15E+05	6.19E+05
BA	1.92E+03	1.75E+01	2.44E+03	1.16E+02	4.60E+04	1.89E+04
SCA	1.98E+03	9.62E+00	1.46E+04	3.75E+03	1.38E+06	5.20E+05
PSO	1.92E+03	2.61E+00	2.35E+03	5.44E+01	1.04E+05	7.32E+04
WOA	1.95E+03	3.49E+01	2.43E+04	1.62E+04	1.10E+06	7.92E+05
	F22		**F23**		**F24**	
	mean	**STD**	**mean**	**STD**	**mean**	**STD**
WGBO	**2.52E+03**	**1.42E+02**	**2.50E+03**	**0.00E+00**	**2.60E+03**	**0.00E+00**
GWO	2.61E+03	1.65E+02	2.63E+03	5.90E+00	2.60E+03	5.97E-04
MFO	3.08E+03	1.96E+02	2.68E+03	3.07E+01	2.68E+03	4.16E+01
BA	3.33E+03	3.05E+02	2.62E+03	2.99E-03	2.66E+03	4.80E+01
SCA	2.96E+03	1.01E+02	2.67E+03	1.00E+01	2.60E+03	3.03E-02
PSO	3.02E+03	1.60E+02	2.62E+03	5.43E-01	2.63E+03	5.24E+00
WOA	1.44E+03	2.69E+02	2.62E+03	4.35E+01	2.61E+03	5.04E+00
	F25		**F26**		**F27**	
	mean	**STD**	**mean**	**STD**	**mean**	**STD**
WGBO	**2.70E+03**	**0.00E+00**	**2.70E+03**	**6.40E-02**	**2.90E+03**	**0.00E+00**
GWO	2.71E+03	3.32E+00	2.74E+03	5.14E+01	3.41E+03	6.18E+01
MFO	2.71E+03	8.78E+00	2.70E+03	1.12E+00	3.70E+03	2.34E+02
BA	2.73E+03	2.19E+01	2.70E+03	2.22E-01	3.65E+03	4.79E+02
SCA	2.73E+03	5.66E+00	2.70E+03	4.89E-01	3.63E+03	3.64E+02
PSO	2.71E+03	5.52E+00	2.80E+03	1.08E-01	3.62E+03	2.76E+02
WOA	2.71E+03	1.54E+01	2.70E+03	1.66E-01	3.81E+03	3.53E+02
	F28		**F29**		**F30**	
	mean	**STD**	**mean**	**STD**	**mean**	**STD**
WGBO	**3.00E+03**	**0.00E+00**	**8.70E+05**	**2.74E+06**	**5.60E+03**	**1.18E+03**
GWO	3.78E+03	1.50E+02	1.91E+05	4.81E+05	6.23E+04	5.24E+04
MFO	3.93E+03	9.51E+01	3.17E+06	4.06E+06	2.79E+04	1.52E+04
BA	5.13E+03	7.03E+02	3.78E+07	5.39E+07	1.40E+04	1.04E+04
SCA	4.62E+03	1.82E+02	8.57E+06	2.94E+06	2.77E+05	8.14E+04
PSO	7.08E+03	5.62E+02	7.48E+04	2.20E+05	1.57E+04	7.16E+03
WOA	4.97E+03	7.81E+02	6.64E+06	4.59E+06	9.99E+04	7.41E+04

Table 3. Comparison of results for different algorithms

	WGBO	GWO	MFO	BA	SCA	PSO	WOA
+/=/-		23/7/0	29/1/0	28/2/0	30/0/0	26/4/0	27/3/0
ARV	**1.27833**	3.606667	4.86	3.94333	5.95	3.91333	4.448333

3. Conclusion

The research and application of GBO is still in its infancy, so there are still many problems to be further studied. Firstly, combining the traditional meta-heuristic algorithm with GBO can better balance the global and local search capabilities and improve the overall optimization potential of GBO. Second, how to apply WGBO to solve multi-objective problems requires a very competitive optimizer. WGBO method is not only a classic effective tool for engineering problems, but also use and evaluate its performance to realize the depth of the feasible solution study scenario, image

processing, feature selection, information fusion, modeling, and the research of wireless sensor network (network), multipath routing, WSN-assisted the opportunity to network, and water pollution prediction, disease diagnosis and social evolution model. Further research is needed in the future research.

References

[1] J. Liang, B. Qu, P. Suganthan, Problem definitions and evaluation criteria for the CEC 2014 special session and competition on single objective real-parameter numerical optimization, 2013.

[2] Mirjalili, S.; Mirjalili, S.M.; Lewis, A. Grey Wolf Optimizer. Advances in Engineering Software.2014. 69. 46-61.

[3] Shinwan, M. Moth–flame optimization algorithm: variants and applications. Neural Comput. Appl. 2020, 32, 9859-9884.

[4] Liu, Q. A novel bat algorithm with double mutation operators and its application to low-velocity impact localization problem. 497 Engineering Applications of Artificial Intelligence. 2020. 90, 103505

[5] Mirjalili, S. SCA: A Sine Cosine Algorithm for solving optimization problems. Knowledge-Based Systems.2016. 96. 120-133.

[6] Hop, D.C.; Van Hop, N.; Anh, T.T.M. Adaptive particle swarm optimization for integrated quay crane and yard truck schedul- 490 ing problem. Computers & Industrial Engineering. 2021. 153, 107075.

[7] Mirjalili, S.; Lewis, A. The Whale Optimization Algorithm. Advances in Engineering Software. 2016. 95. 51-67.

[8] García, S., Fernández, A., Luengo, J., & Herrera, F. Advanced nonparametric tests for multiple comparisons in the design of experiments in computational intelligence and data mining: Experimental analysis of power. Information Sciences, 2010,180, 2044-2064.

[9] Derrac, J., García, S., Molina, D., & Herrera, F. A practical tutorial on the use of nonparametric statistical tests as a methodology for comparing evolutionary and swarm intelligence algorithms. Swarm and Evolutionary Computation, 2011,1, 3-18.