

Battle royale optimizer with a new movement strategy

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Abstract. Gamed-based is a new stochastic metaheuristics optimization category that is inspired by traditional or digital game genres. Unlike SI-based algorithms, individuals do not work together with the goal of defeating other individuals and winning the game. Battle royale optimizer (BRO) is a Gamed-based metaheuristic optimization algorithm that has been recently proposed for the task of continuous problems. This paper proposes a modified BRO (M-BRO) in order to improve balance between exploration and exploitation. For this matter, an additional movement operator has been used in the movement strategy. Moreover, no extra parameters are required for the proposed approach. Furthermore, the complexity of this modified algorithm is the same as the original one. Experiments are performed on a set of 19 (unimodal and multimodal) benchmark functions (CEC 2010). The proposed method has been compared with the original BRO alongside six well-known/recently proposed optimization algorithms. The results show that BRO with additional movement operator performs well to solve complex numerical optimization problems compared to the original BRO and other competitors.

Keywords: Battle Royale Optimizer, Metaheuristic, Game-based optimization.

1 Introduction

Metaheuristic is a multipurpose algorithm that solves problems in an iterative manner, trying to find the best feasible option among a number of applicant solutions with a quality measure [1]. Metaheuristic optimization methods have attracted the attention of scientists and engineers from a number of disciplines, as they serve a major role both in scientific and industrial use in many practical challenges [2]. Over the last three decades, various optimization techniques have been proposed on various sources of inspiration. Battle royale optimization (BRO) [3] is a recently proposed optimization algorithm that is motivated by a digital games genre called the "royal battle". BRO is a population-based optimization algorithm that simulates the deathmatch play mode of Player Unknown's Battlegrounds (PUBG) [4]. BRO aims at solving single-objective optimization in continuous problem spaces [5]. Although several optimization algorithms have been introduced in recent years, the BRO algorithm is of particular im-

portance among these algorithms. This is because this algorithm has opened a new horizon for metaheuristic algorithms. Before this algorithm was developed, metaheuristic algorithms consisted of three main categories: Evolutionary algorithms (EA); Swarm Intelligence (SI); and physical phenomena algorithms. But BRO introduced a new metaheuristic category called game-based.

EA-based algorithms are inspired by Darwin's theory of biological Evolution, mimicking concepts of reproduction, mutation, and selection to achieve the best possible solution. Genetic Algorithm (GA) [6], Evolution Strategies (ES) [7], Tabu Search (TS) [8], Simulated-Annealing (SA) [9], Differential Evolution (DE) [10], Biogeography-Based Optimizer (BBO) [11], Forest Optimization Algorithm (FOA) [12], etc. can be mentioned as the most well-known EA paradigms.

SI-based algorithms mimic the collective behavior of various kinds of the living being, such as humans, animals, insects, single-cells, etc., in the population. Although not every individual is intelligent alone, their collective behavior leads to an intelligent search scheme. Some of well-known and recently developed SI-based algorithms are Particle Swarm Optimization [13], Ant colony optimization [14], Cat swarm optimization [15], Artificial Bee Colony(ABC)[16], Cuckoo Search(CS) [17], Firefly Algorithm (FA) [18], Animal migration optimization [19], Dolphin echolocation (DE) [20], Chimp optimization algorithm (COA) [21], Human mental search (HMS) [22], and Selfish Herd Optimizer (SHO) [23], Group Search Optimizer (GSO) [24] as well as others.

To reach the optimal solution physics-based algorithms make use of the laws of physics such as gravitational force, inertia force, electromagnetic force, etc. The movement and communication between populations are conducted by means of these rules [25]. Examples of physics-based methods are Quantum stochastic optimization (QSO) [26], Central Force Optimization (CFO) [27], Gravitational Search Algorithm (GSA)[28], Charged System Search (CSS) [29], Black Hole (BH) [30], Optics inspired optimization (OIO) [31], Water Evaporation Optimization (WEO) [32], Yin-Yang-Pair Optimization (YYPO)[33], Thermal exchange optimization [34], Electromagnetic Field Optimization (EFO) [35], Billiards-inspired optimization algorithm (BOA) [36], and others.

Exploration and exploitation are two critical factors in the success of an optimization algorithm. Every optimization algorithms have their own strategy for performing exploration and exploitation mechanism [28]. In order to deliver a successful outcome in an optimization algorithm, the balance between exploration and exploitation must be maintained. Exploration aims to escape from local optima by exploring among new solution-candidates in the unvisited areas of problem space. On the other hand, exploitation focuses on the area where exploitation focuses on the best solution to search more accurately. E.g., in PSO p_{best} provides exploitation alongside c_1 coefficient parameter while g_{best} provides exploration alongside c_2 coefficient parameter. Moreover, in some cases, an additional local search step is applied to enhance exploitation [37].

According to the famous mathematician Leonhard Euler, everything in nature is ultimately either minimized or maximized. Whether plants or animals, living beings have been able to adapt to the environment over time, and they found a way to survive. Nature has always seen and will continue to witness far-reaching changes; as a result,

nature can be exposed to new changes and problems that must find new solutions to adapt to them. In fact, the scientific and engineering community is not unlike nature: every day, new issues may arise that at times require a new method of solution. Hence, it makes sense to be inspired by nature to develop optimization algorithms to minimize or maximize the problems. This claim could be a confirmation of the No Free Lunch (NFL) theorem [38]. NFL is a response to critics who claim that there are many optimization algorithms and that there is no need for new algorithms. The NFL proves that an optimization algorithm may not outperform others in meeting all optimization challenges. There is no heuristic algorithm yet that solves all optimization problems by providing superior performance. Therefore, it is necessary to propose new approaches as well as to improve existing ones.

BRO is a recently-proposed population-based metaheuristic optimization algorithm for continuous optimization problems that is inspired by strategies of multiplayer video game genre (Battle royale games). There are various kinds of Battle Royale games, the most important of which are Player Unknown's Battlegrounds (PUBG) [4], Call of Duty: Warzone [39], Apex Legends [40], Counter-Strike: Global Offensive [41], and Ring of Elysium [42]. However, these games are not very different from each other in game strategy. In fact, BRO mimics the solo-deathmatch mode of PUBG.

Like other stochastic algorithms, search agents randomly distributed over the problem space using a uniform distribution. BRO generates randomly N solutions using Eq. 1.

$$x_{i,d} = r(ub_d - lb_d) + lb_d \quad (1)$$

where $i = 1 \dots N$, $d = 1 \dots D$. N is the number of possible solutions in the population. D is the dimension of the problem space. lb_d and ub_d are the lower and the upper bounds of d^{th} dimension, respectively. In the following, the fitness value of each solution is compared to the fitness value of the nearest neighbor with regard to the Euclidean distance. And then, the solution with the better fitness value will be declared the winner and the other the loser. Next, the loser one will be damaged, and the damage count of it will be increased by one. On the contrary, the damage of the winner will be reset to zero. The operator is expressed as: $x_{dam,damage} = x_{dam,damage} + 1$ and $x_{vic,damage} = 0$, where dam and vic are the indexes of the loser and winner solutions, respectively. Meanwhile, loser one attempts to move toward the best solution to locate the better position. The new position vector of the loser solution can be calculated by Eq. 2.

$$x_{dam,d} = x_{dam,d} + r(x_{best,d} - x_{dam,d}), \quad (2)$$

where r is a randomly-generated number from a uniform distribution [0,1] and $x_{dam,d}$ is the position of the damaged solution in d^{th} dimension. Moreover, If a solution has a worse fitness value than his neighbor through a pre-determined number of times in a row, it will not be a solution candidate. For this purpose, the solution will be eliminated from the set of the solutions and will be replaced by a random one according to Eq. 1. It is worth noting that to provide exploitation, the problem space shrinks down towards the best solution in every Δ iteration. The

initial value for Δ is calculated per $\Delta = \text{MaxCicle}/\log_{10}(\text{MaxCicle})$. Then, it will be updated through $\Delta = \Delta + \text{round}(\frac{\Delta}{2})$. MaxCicle is the maximum number of iteration herein. To put this concept lower and upper bound of each problem dimension will shrink towards the best solution as follows:

$$\begin{aligned} lb_d &= x_{best,d} - SD(\bar{x}_d) \\ ub_d &= x_{best,d} + SD(\bar{x}_d) \end{aligned} \quad (3)$$

where $SD(\bar{x}_d)$ indicates the standard deviation of all solutions of the population in d^{th} dimension and $x_{best,d}$ refers to the position of the best solution ever found.

2 A new movement strategy

The new movement strategy is characterized by keeping the individual motion and the expansion of the search area. In doing so, it can reflect changes in individual speed. In this case, by using an additional parameter, the individual in motion updates and maintains another parameter to use in the next iteration. This parameter is randomly generated at first and is later updated. Subsequently, its value would be closely associated with an individual search capability. The greater the value of the movement operator, the greater the individual speed will be. To do a global search, the individuals would have a larger step. Their global capacity for optimization is strong, and their capacity for local search is weak. To do a local search, the individuals would have a smaller step. Their global capacity for optimization is weak, and their capacity for local search is strong. The smaller the value of the movement operator, the smaller the size of the individual step will be. If the movement step is too large, an algorithm can fail to achieve or converge to the optimal solution, resulting in the algorithm not converging.

For the moving an individual towards the best one the Eq. 2 has been reformulated as follows:

$$\begin{aligned} \lambda_{dam,d} &= r_1 x_{best,d} + r_2 (\lambda_{dam,d} - x_{dam,d}), \\ x_{dam,d} &= \lambda_{dam,d} + x_{dam,d} \end{aligned} \quad (4)$$

where r_1 and r_2 are two randomly-generated numbers from a uniform distribution [0,1] and $\lambda_{dam,d}$ is also a combination randomly-generated numbers from a uniform distribution [0,1] that will be updated through the iterations. This modified moving strategy provides more randomness in both exploration and exploitation.

Table 1. Unimodal benchmark test functions

Function	Name	Range	Shift position
$f_1(\mathbf{x}) = \sum_{i=1}^n x_i^2$	Sphere	[-100,100]	[-30, -30, ..., -30]
$f_2(\mathbf{x}) = \sum_{i=1}^n x_i + \prod_{i=1}^n x_i $	Schwefel 2.20	[-10,10]	[-3, -3, ..., -3]
$f_3(\mathbf{x}) = \sum_{i=1}^n \left(\sum_{j=1}^i x_j \right)^2$	Rotated hyper-ellipsoids	[-100,100]	[-30, -30, ..., -30]
$f_4(\mathbf{x}) = \max_{i=1, \dots, n} x_i $	Schwefel 2.21	[-100,100]	[-30, -30, ..., -30]
$f_5(\mathbf{x}) = \sum_{i=1}^{n-1} \left[100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2 \right]$	Rosenbrock	[-30,30]	[-15, -15, ..., -15]
$f_6(\mathbf{x}) = \sum_{i=1}^n ([x_i + 00.5])^2$	Step	[-100,100]	[-750, -750, ..., -750]
$f_7(\mathbf{x}) = \sum_{i=1}^n ix_i^4 + rand[0,1)$	Quartic	[-128,128]	[-25, -25, ..., -25]

3 Experimental results and performance evaluation

A comprehensive experimental evaluation and comparison were performed to evaluate the performance of the BRO with a random inertia weight. Like the original BRO well-known PSO (Particle Swarm Optimization) algorithm and five recent proposed optimization algorithms: ALO (The Ant Lion Optimizer) [43], MFO (Moth-flame optimization algorithm) [44], MVO (Multi-Verse Optimizer) [45], SCA (A Sine Cosine Algorithm) [46], and WOA (The Whale Optimization Algorithm) [47] have been selected as competitors. Moreover, the original BRO has also been used in comparisons. The parameters for the control of all algorithms have been set in the initial papers according to recommendations. In addition, all algorithms were carried out and implemented in MATLAB and Conducted on a Core i7-7700 HQ 2.81 Processor with 32 GB of RAM. This paper also uses 19 well-known benchmark functions for comparison that include unimodal and multi-modal properties, like the original study. All these functions have been listed in Tables 1–3. For every algorithm, the maximum number of iteration and population size is 500 and 100, respectively. Also, the threshold value for maximum damage is 3, and both r_1 and r_2 are randomly generated number uniformly distributed in the range [0,1]. All of the following test results are achieved by taking an average of 25 independent runs each. In addition, the median and standard variation of the fitness evaluation values are used as performance measures in 25 independent runs. Tables 4, 5, and 6 for all unimodal and multimodal test functions, have provided the experimental results.

Table2. Multimodal benchmark test functions

Function	Name	Range	Shift position
$f_8(\mathbf{x}) = \sum_{i=1}^n x_i \sin(\sqrt{ x_i })$	Schwefel	[-500,500]	[-300, ..., -300]
$f_9(\mathbf{x}) = 10n + \sum_{i=1}^n (x_i^2 - 10 \cos(2\pi x_i))$	Rstrigin	[-5.12, 5.12]	[-2, ..., -2]
$f_{10}(\mathbf{x}) = -20 \cdot \exp(-0.2 \sqrt{\frac{1}{n} \sum_{i=1}^n x_i^2})$ $-\exp(\frac{1}{n} \sum_{i=1}^n \cos(2\pi x_i)) + 20 + \exp(1)$	Ackley	[-32, 32]	
$f_{11}(\mathbf{x}) = 1 + \sum_{i=1}^n \frac{x_i^2}{4000} - \prod_{i=1}^n \cos(\frac{x_i}{\sqrt{i}})$	Griewank	[-600, 600]	[-400, ..., -400]
$f_{12}(\mathbf{x}) = \frac{\pi}{n} \times \{10 \sin^2(\pi y_1) + \sum_{i=1}^{n-1} (y_i - 1)^2$ $[1 + 10 \sin^2(\pi y_{i+1})] + (y_n - 1)^2\} +$ $\sum_{i=1}^n u(x_i, 10, 100, 4)$ $y_i = 1 + \frac{1}{4}(x_i + 1)$	penalized	[-50, 50]	[-30, ..., -30]
$f_{13}(\mathbf{x}) = 0.1 \{ \sin^2(3\pi x)$ $+ (x_i - 1)^2 (1 + \sin^2(3\pi y))$ $+ (x_n - 1)^2 (1 + \sin^2(2\pi x_n)) \}$ $+ \sum_{i=1}^n u(x_i, 5, 100, 4)$	Levi	[-50, 50]	[-100, 100]

Table3. Multimodal benchmark test functions with fixed- dimension

Function	Dim	Range
$f_{14} = \left(\frac{1}{500} + \sum_{j=1}^{25} \frac{1}{j + \sum_{i=1}^2 (x_i - a_{ij})^6} \right)^{-1}$	2	[-65,65]
$f_{15} = \sum_{i=1}^{11} \left[a_i - \frac{x_1(b_i^2 + b_i x_2)}{b_i^2 + b_i x_3 + x_4} \right]^2$	4	[-5,5]
$f_{16} = 4x_1^2 - 2.1x_1^4 + \frac{1}{3}x_1^6 + x_1x_2 + 4x_2^2 + 4x_2^4$	2	[-5,5]
$f_{17} = \left(x_2 - \frac{5.1}{4\pi^2}x_1^2 + \frac{5}{\pi}x_1 - 6 \right)^2 + 10 \left(1 - \frac{1}{8\pi} \right) \cos(x_1) + 10$	2	[-5,5]
$f_{18} = [1 + (x_1 + x_2 + 1)^2(19 - 14x_1 + 3x_1^2 - 14x_2 + 6x_1x_2 + 3x_2^2)] \times [30 + (2x_1 - 3x_2)^2 \times (18 - 32x_1 + 12x_1^2 + 48x_2 + 36x_1x_2 + 27x_2^2)]$	2	[-2,2]
$f_{19} = - \sum_{i=1}^4 c_i e^{(-\sum_{j=1}^3 a_{ij}(x_j - p_{ij})^2)}$	3	[1,3]

Table 4 Results for unimodal benchmark test functions of 30 dimension

F	M-BRO	BRO	PSO	ALO	MFO	MVO	SCA	GOA
F1 mean	1.2012e-26	3.0353e-09	8.131e-08	1.e-06	0.937433	0.24190	0.139829	1028.242
Std	1.6456e-26	4.1348e-09	1.567e-07	1.e-06	0.547602	0.04815	0.213883	2921.282
time	3.598942	3.536958	1.1516	76.82223	0.5428634	0.7795	0.213883	1264.051
F2 mean	1.3350e-15	0.000046	0.1282	20.52849	28.501319	0.29813	0.000979	77.97797
Std	9.8358e-16	0.000024	0.2889	31.56666	19.846522	0.07011	0.001209	48.421113
time	3.290291	3.577353	1.1460	77.20241	0.5510458	0.71363	0.5723780	1332.949
F3 mean	4.2811e-08	54.865255	103.5336	127.4139	12432.852	13.2258	1524.3665	5095.518
Std	6.2916e-08	16.117329	77.8071	43.86708	8927.4874	5.38360	1339.0129	5875.806
time	3.829758	3.710890	1.1226	77.78005	1.449506	1.62891	1.436205	1206.811
F4 mean	7.7175e-07	0.518757	3.0470	8.659458	30.626058	0.52880	16.26705	1.775508
Std	1.4126e-06	0.403657	1.9104	3.145536	10.680434	0.22757	9.442185	0.989782
time	3.834288	3.532575	1.1399	77.5049	0.5653759	0.74207	0.5887966	1303.754
F5 mean	27.03186	99.93684	59.0941	70.59842	1128.7042	329.447	782.05773	754.8616
Std	0.4024602	82.862358	44.7770	71.72374	1327.9809	566.273	2102.6807	2748.332
time	5.096510	3.948993	1.2316	77.04758	0.6677657	0.8423	0.720768	423.1110
F6 mean	2.257257	2.8731e-08	9.332e-08	1.e-06	1601.2818	0.23379	4.097225	0.000003
Std	0.3160390	1.8423e-08	2.255e-07	1.e-06	3741.6075	0.05323	0.599685	0.000002
time	4.221259e	3.551993	1.1685	77.13036	0.5411606	0.74088	5.861539	424.5775
F7 mean	7.8361e-04	0.000368	0.0215	0.023584	2.211140	0.00798	0.021428	4.330057
Std	5.8031e-04	0.000094	0.0097	0.00849	3.461601	0.00327	0.01812	9.45593
time	5.196062e	4.307858	1.5415	77.5254	1.082169	1.26860	1.102313	1242.990

Table 4 proves that the modified BRO provides the best results in six out of seven unimodal functions with respect to mean and std. It is clear that there is a great improvement in the results. As it is clear, GOA performs worst among the others. Also,

Table 5 shows that in five of seven multimodal functions, BRO outperforms others in terms of mean and outperforms five out of seven respect to std. As is evident from these tables, there is a great improvement in results. Such that, for F1, the mean value of the proposed method is $1.20128e-26$, while for the original BRO is $3.0353e-09$. Coming to the fixed-dimension multimodal functions, the modified BRO has not performed better in just one case (F14). In the rest of the function, the proposed method provides competitive results.

Table 5 Results for multimodal benchmark test functions of 30 dimension

F		M-BRO	BRO	PSO	ALO	MFO	MVO	SCA	GOA
F8	mean	-4.5130e+03	-7035.210	-9.39e+31	-5601.864	-9439.105	-7872.021	-4118.072	-6759.6244
	Std	5.3803e+02	712.3326	4.22e+32	362.17167	933.4169	651.30106	295.8680	899.29158
	time	3.871863	3.782519	1.1632	77.28404	0.705079	0.7452922	0.732390	1259.423
F9	mean	0	48.27535	54.2471	60.851573	107.59104	108.04483	17.584379	174.76975
	Std	0	14.09458	13.4287	22.120831	24.913857	32.191667	20.95633	29.134588
	time	3.811548	3.771521	1.2822	77.06642	0.621141	0.8954284	0.635833	1270.283
F10	mean	3.3573e-14	0.350724	0.9906	2.053675	6.363405	0.712974	10.13371	3.366269
	Std	3.595e-14	0.688712	0.8038	0.796278	8.534955	0.693826	9.537759	4.154672
	time	3.646655	3.784324	1.2443	77.20121	0.647817	0.9157972	0.684157	1209.365
F11	mean	0	0.001373	0.0089	0.010494	0.751211	0.479614	0.455533	7.231566
	Std	0	0.010796	0.0113	0.016548	0.179238	0.159060	0.275454	23.778806
	time	3.84395	3.844791	1.2318	77.07877	0.735585	1.028005	0.775249	1213.085
F12	mean	0.130451	0.369497	30.4105	6.933983	1.734171	0.553024	1.184349	4323306.37
	Std	2.8956e-02	0.601450	9.4299	3.807565	1.328050	0.624414	1.270975	1616521.88
	time	5.694005	5.278253	1.3266	78.24491	1.965486	2.268537	2.036552	1214.762
F13	mean	0.628109	0.000004	41.1520	0.006889	2.047761	0.032335	19.14310	18404721.8
	Std	0.110578	0.000020	9.6473	0.009962	1.909983	0.013044	71.92344	81308523.2
	time	3.304954	3.303456	1.3337	78.24868	1.986649	2.291993	2.154423	1191.996

Table 6 Results for fixed-dimension multimodal benchmark test functions

F		M-BRO	BRO	PSO	ALO	MFO	MVO	SCA	GOA
F14	mean	0.998004	0.9980	0.9980	1.157048	0.998004	0.998004	1.077373	1.791015
	Std	0.6285483	0	0	0.371931	0	4.4661e-12	0.396819	1.144130
	time	3.565870	3.60161	2.7190	8.726093	0.282815	2.960769	0.289890	824.6873
F15	mean	04.5511e-04	0.00047	0.0005105	0.001544	0.000748	0.000624	0.000845	0.007727
	Std	3.00125e-04	0.00026	0.003323	0.003925	0.000270	0.000315	0.000398	0.008465
	time	2.486470	2.36244	0.9858	1.140260	0.277466	0.3253819	0.272637	158.6677
F16	mean	-1.0316	-1.0316	-1.0316	-1.03162	-1.03162	-1.031628	-1.031619	-1.03162
	Std	8.1149e-06	5.995e-16	6.798e-16	6.872e-16	6.79e-16	4.7670e-08	0.000007	7.194e-16
	time	2.015800	1.950645	0.8377	6.266332	0.25199	0.2871051	0.242102	79.82012
F17	mean	0.397887	0.397887	0.3979	0.397887	0.39788	0.397887	0.398227	0.410236
	Std	0	0	0	0	7.42e-16	0	0.000260	0.064367
	time	1.959311	1.975396	0.7929	5.986799	0.21526	0.2524479	0.206958	117.7970
F18	mean	3.000000	3.000000	3.000000	3.000000	3.000000	3.000001	3.000002	3.000000
	Std	2.5895e-16	2.5895e-16	1.344e-15	9.012e-14	1.88e-15	3.3333e-07	0.000003	0.000101
	time	1.979300	2.104709	0.7916	6.17052	0.20697	0.2461370	0.192042	84.81287
F19	mean	-3.86208	-3.86278	-3.8628	-3.86278	-3.8627	-3.862782	-3.856386	-3.8566
	Std	5.4290e-04	2.006e-15	2.266e-15	6.225e-15	2.266e-15	8.0539e-08	0.003206	0.0032
	time	2.884435	4.461555	1.0814	9.011699	0.302513	0.3353661	0.299619	167.7970

4 Conclusion

In this article, a modified BRO with a new movement operator has been proposed to provide a better balance between exploration and exploitation. Within the modified BRO, there are no user-set parameters, nor are kinds of other user-intervention required. At the same time, this algorithm maintains the complexity of the original one. Experiments were performed on 19 well-known (unimodal and multimodal) benchmark functions (CEC 2010). To verify the performance of the modified BRO, the original BRO, besides the well-known PSO algorithm and five recent proposed optimization algorithms ALO, MFO, MVO, SCA, and GOA, were also tested for comparison. Results indicate that the BRO with random inertia weight performs well to address complex numerical optimization problems, compared to the original BRO and other competitors.

Conflict of interest Authors declare that they have no conflict of interest.

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