

An Improved Zebra Optimization Algorithm

Yuqi Liu

Abstract—Zebra optimization algorithm (ZOA) is a heuristic algorithm proposed in 2022. Although ZOA is popular because of its simple structure, it has the disadvantage of easily falling into local optimal solutions and running slowly. To overcome these shortcomings, an improved zebra optimization algorithm (IZOA) is proposed. In order to improve the running speed of ZOA and the ability to obtain the optimal solution, Aquila Optimizer and Levy flight strategy are introduced into IZOA. Opposition-based learning technique is introduced into IZOA, expanding the diversity of the population. The effectiveness and usefulness of IZOA is tested using CEC2019. In CEC2019, IZOA is superior to or equivalent to other test algorithms. Experimental results show that IZOA is more effective and practical than other algorithms in solving practical problems.

Index Terms— Zebra optimization algorithm (ZOA); Aquila Optimizer (AO); Levy flight;

I. INTRODUCTION

Swarm intelligence optimization algorithm is a new-fashioned optimization method, which simulates various group behaviours of social animals and utilizes information interaction between individuals in the group to achieve the purpose of optimization. At present, the popular swarm intelligence algorithms are Zebra optimization algorithm [1], Aquila Optimizer [2], Subtraction-average-based optimizer [3], Whale optimization algorithm [4], Nutcracker optimizer [5], Spider wasp optimizer [6] and Kepler optimization algorithm [7].

ZOA is a heuristic algorithm proposed in 2022, which inspired by the predatory and defensive behaviour of zebras in nature. ZOA is popular because of its simple algorithmic structure, and several studies have been proposed. In [8], an improved zebra optimization algorithm (IZOA) was proposed by Wenmin He in 2024. In order to avoid the local optimal solution, IZOA uses adaptive oscillation weights to replace the random operators of the original ZOA. Nguyen Duc Huy Bui proposed an improved zebra optimization algorithm (IZOA), which added the levy flight strategy to IZOA. In order to improve the performance of ZOA, a function that does not depend on the number of interactions was introduced into IZOA to replace the exploitation strategy. Finally, a problem of transmission expansion planning was resolved by CZOA [9]. In [10], a modified ZOA (CZOA) was proposed by Dama. CZOA introduced the chaotic sinusoidal map into ZOA for increasing the exploitation and exploration ability. In [11], Ali H.Mhmoed introduced the ZOA into an algorithm, which control the speed of the electric vehicle system. ZOA is introduced into the power system to maintain a stable voltage distribution

[12]. Sarah Alhammad adopted ZOA to deal with the machine translation problem of MRI images [13]. In [14], The authors use ZOA to fine-tune recommended controller parameters for the grid. Zare et al. apply ZOA to the coefficient optimization problem of offshore fixed platform controller [15].

ZOA still has many defects, such as low initial population diversity and easy to fall into local optimal solutions. Therefore, ZOA needs further improvement.

To overcome the above shortcomings, this paper proposes an improved Zebra algorithm (abbreviated as IZOA) and introduces three strategies to improve the accuracy and effectiveness of ZOA. The reverse learning technique and Levy flight technique are used to increase the diversity of the population, expand the global search range, and avoid falling into the local optimal solution. AO algorithm is introduced to improve the running speed and optimize the ability of obtaining the optimum solution. To testify the practicability and effectiveness of the IZOA, IZOA is used to find the optimal solution of 20 benchmark functions and CEC2019 and to solve a learning path recommendation problem. Finally, experiments show the effectiveness and practicability of IZOA.

The main contributions of this paper are as follows:

1. Opposition-based learning technique is introduced into ZOA, which increase the diversity of the initial population.
2. Levy flight strategy is introduced to avoid the dilemma of local optimal solution and better conduct global search.
3. To avoid falling into local optimal solutions, Aquila Optimizer (AO) is introduced in IZOA instead of (1).

II. THE PROPOSED ALGORITHM

A. Zebra Optimization Algorithm (ZOA)

The first strategy: foraging behavior. In the first strategy, population members of ZOA are updated based on foraging behavior of zebras. In ZOA, the best member of the population is called the pioneer zebra, which leads the rest of the group to its location in the search area. The first strategy can be described as follows:

$$x_{i,j} = rand \times (UB_j - LB_j) + LB_j, \quad (1)$$

$$i = 1, 2, \dots, N \quad j = 1, 2, \dots, Dim$$

$$X_i = \begin{cases} x_i^{new,P1}, & F_i^{new,P1} > F_i; \\ X_i, & else, \end{cases} \quad (2)$$

where $x_{i,j}$ represents the value of the j th question variable posed by the i th zebra, r is a random value from [0.1]. $x_{i,j}^{new,P1}$ represents the new position of the i th zebra and $x_{i,j}^{new,P1}$ represents its j th dimension value. PZ_j represents the best individual in j th dimension. I can be expressed as follow:

$$I = round(1 + rand) \quad (3)$$

Manuscript received March 17, 2025

Yuqi Liu, School of computer science and technology, Tiangong University, Tianjin, China.

An Improved Zebra Optimization Algorithm

where rand represents random quantity from 0 to 1. The range of I is either 1 or 2 therefore.

The second strategy: defense strategy against predators. In the phase, the individual positions of ZOA are updated by simulating the defense tactics against predators of zebras. The zebra's main predator is the lion. Zebras defend themselves against various predators in different ways. The best way for zebras to protect themselves against the attack from a lion is to use a zigzag running tactic and an escape with a sudden turn at full speed. While. Zebras have higher levels of aggression when faces with other small predators. In ZOA, one of the following two scenarios is assumed to occur with equal probability.

(i): exploitation (escape strategy)

This strategy leads them to escape the area where they are being attacked for avoiding the further risk. This keeps the zebra from being eaten by lions. This strategy can be expressed as follow:

$$x_{i,j}^{new,P2} = x_{i,j} + R \cdot (2r-1) \cdot \left(1 - \frac{t}{T}\right) \cdot x_{i,j}, \quad (4)$$

$$P_s \leq 0.5$$

where $x_{i,j}^{new,P2}$ is the new status of the i th zebra based on escape strategy. R represents the constant of 0.01. r is a random value from $[0,1]$. T and t are the maximum iteration number and the current iteration, respectively. P_s is the probability of choosing escape strategy that is random number from $[0,1]$.

(ii): exploitation (offensive strategy)

When other animals attack a zebra, the other zebras move to the attacked zebra and create a defensive structure. (5) can be expressed this strategy. When updating the zebra position, if the zebra has a better improvement result on the objective function value at the new position, the new position is accepted. This update strategy can be represent using (6).

$$x_{i,j}^{new,P2} = x_{i,j} + r \cdot (AZ_j - I \cdot x_{i,j}), P_s > 0.5 \quad (5)$$

$$X_i = \begin{cases} x_i^{new,P2}, F_i^{new,P2} > F_i; \\ X_i, else, \end{cases} \quad (6)$$

where $X_i^{new,P2}$ represents the updates of the i th zebra according to the offensive strategy, and $x_{i,j}^{new,P2}$ represents the j th dimension value for $X_i^{new,P2}$. AZ is the position of the attacked zebra. I can compute by using (3). $F_i^{new,P2}$ is the objective function value for $X_i^{new,P2}$.

B. Opposition-based learning (OBL)

Tizhoosh proposed the opposition-based learning strategy in 2005 [25]. In recent years, OBL technology is increasingly used to improve the performance of various algorithms. OBL technology works by comparing the original solution with the opposite solution to improve the search process. In the process of the algorithm, the fitness functions are used to evaluate the original solution and the opposite solution. Then, the best solution is kept and the other solution is ignored. The opposite value X_{obl} can be expressed as follow:

$$X_{obl} = ub + lb - X \quad (7)$$

where $X \in [lb, ub]$. ub and lb are upper boundary and lower boundary, respectively.

If X is a multi-valued vector: $X = (X_1, X_2, \dots, X_n)$. Then, the opposite value X_{obl} can be expressed as follow:

$$X_j^{obl} = ub_j + lb_j - X_j \quad (8)$$

C. Levy flight strategy

The Levy flight strategy is a random behavior strategy used to simulate step size and direction during a random walk or search. It simulates how organisms move in certain situations when searching for food or resources. Levy flight strategy has applications in some natural search and optimization problems, such as in the study of animal foraging behavior, as well as in some meta-heuristic algorithms and optimization algorithms. It can be used to simulate random exploration in the search space, sometimes help algorithms avoid getting trapped in local optimal solutions and better explore the global search space.

D. Improved Zebra Optimization Algorithm (IZOA)

In this section, an improved zebra optimization algorithm (IZOA) is described.

To increase the diversity of the population, the opposition-based learning strategy is introduced in IZOA. In order to expand the scope of global search and avoid falling into local optimal solutions, an improved aquila optimizer is introduced into IZOA to replace the (1). Inspired by the AO, in order to avoid falling into the local optimal solution and better explore the global search space in the late stage of the algorithm, Levy flight technology is introduced into IZOA.

An improved foraging behavior strategy can be shown as follow:

$$x_{i,j}^{new,P1} = PZ_j \times \left(1 - \frac{t}{T}\right) + \text{mean}(X(i,:) - PZ_j) \times r \quad (9)$$

where t and T are the t -th iteration and the maximum iteration number, respectively. $r \in [-2,2]$.

An improved offensive strategy can be shown as follow:

$$x_{i,j}^{new,P2} = QF \times PZ_j + G_1 \times \text{Levy}(D) + \cos\left(\left(\frac{pi}{2}\right) \times \left(\frac{t}{T}\right)\right) \times (AZ - I \times x_{i,j}) \quad (10)$$

$$QF(t) = t^{\frac{2 \times \text{rand} - 1}{(1-T)^2}} \quad (11)$$

$$G_1 = 2 \times \left(1 - \left(\frac{t}{T}\right)\right) \quad (12)$$

The pseudo of IZOA is expressed in Algorithm 2.

After initializing the initial population, the population of opposition-based learning and the algorithm parameters, the objective function values and the position of the zebra are calculated (lines 1-3). When $t \leq T$, the zebra leader is updated (line 5). When $i \leq N$, the foraging behavior is executed, the zebras' position and their opposite position are updated by using (9) and (8) (lines 8-9). Then the fitness function value and zebra are updated (lines 10-11). If $P_s < 0.5$, the escape strategy is executed, the zebras' position and their opposite position are updated by using (4) and (8) (lines 15-16). If $P_s \geq 0.5$, the offensive strategy is executed, the zebras' position and their opposite position are updated by using (10) and (8)

(lines 19-20). Finally, the position of zebras and the best solution are updated (lines 22-24).

Algorithm 2. IZOA

```

Initialization phase:
1 Initialize the population  $X_i$  and the opposite value  $X_{obl}$ 
  of the IZOA.
2 Initialize the parameters of IZOA.
3 Initialize the position of zebras and calculate the fitness
  function values.
4 for  $t = 1: T$ 
5     Update zebra leader (PZ).
6     for  $i = 1: N$ 
7         /* strategy I: foraging behavior */
8         Update the new position of the  $i$ th zebra using
          (9)
9         Update the opposite position using (8)
10        Compute the fitness function values of  $X_i$  and
           $X_{obl}$ .
11        Update the  $i$ th zebra.
12        /* strategy II: defense strategy against
          predators */
13        if  $P_s < 0.5$ ,  $P_s = \text{rand}$ 
14        /* Exploitation (escape strategy) */
15            Update the new position of the  $i$ th zebra
              using (4)
16            Update the opposite position using (8)
17        else
18            /* Exploitation (offensive strategy) */
19            Update the  $i$ th zebra using (10)
20            Update the opposite position using (8)
21        end if
22        Update the  $i$ th zebra using (6)
23    end for  $i = 1: N$ 
24    Update the best solution ( $X_{best}$ ).
25 end for  $t = 1: T$ 
26 Return best solution ( $X_{best}$ )
  
```

The complexity of IZOA is shown as follow. The stage of IZOA include initialization, calculation of fitness value, and updating the location of zebras. The complexity of IZOA initialization preparation is $O(N \times m)$, where N is the total number of zebras and m is the number of problem variables. In the stage of calculation of fitness value and updating the location of zebras, because the individual is renewed in two stages, the complexity of update process is $O(2 \times N \times m \times T)$, where T is the maximum iteration number. So, $O(\text{IZOA}) = O(\text{initialization}) + O(\text{calculation of fitness}) + O(\text{updating the location of zebras}) = O(N \times m \times (1 + 2 \times T))$.

III. EXPERIMENT SETUP

A. Parameter Setup of compared algorithm and IZOA

The proposed IZOA will be compared with ZOA, WOA, GWO and SABO. All compared algorithm and IZOA are tested against CEC2019. For ZOA, parameters are set up as follows:

- P_s is a rand number from 0 to 1.
- I is either 1 or 2.
- $R = 0.1$.

For WOA, parameters are set up as follows:

- $a = 2 - t \times (2/T)$
- $a_2 = -1 + t \times ((-1)/T)$
- r_1 and r_2 are random number from $[0,1]$.
- $b = 1$
- $C = 2 \times r_2$

For GWO, parameters are set up as follows:

- $A_1 = 2 \times (2 - t \times (2/T)) \times \text{rand}() - (2 - t \times (2/T))$
- $C_1 = 2 \times \text{rand}()$
- r_1 and r_2 are random number from $[0,1]$.

For SABO, parameters are set up as follows:

- I is a random value from $[1,2]$

For IZOA, parameters are set up as follows:

- I is either 1 or 2.
- P_s is a random number from $[0,1]$
- $R = 0.1$

B. CEC2019

To further test the quality of IZOA, all compared algorithm and IZOA are also test against all functions in CEC2019.

Table 1 displays the all functions in 2019.

Table 1 all functions in CEC2019

No	Description	Dim	Range	f_{min}
F_1	Storn's Chebyshev Polynomial Fitting Problem	9	[-8192, 8192]	1
F_2	Inverse Hilbert Matrix Problem	16	[-16384, 16384]	1
F_3	Lennard-Jones Minimum Energy Cluster	18	[-4,4]	1
F_4	Rastrigin's Function	10	[-100,100]	1
F_5	Grienwank's Function	10	[-100,100]	1
F_6	Weierstrass Function	10	[-100,100]	1
F_7	Modified Schwefel's Function	10	[-100,100]	1
F_8	Expanded Schaffer's F6 Function	10	[-100,100]	1
F_9	Happy Cat Function	10	[-100,100]	1
F_{10}	Ackley Function	10	[-100,100]	1

In all experiments, the population size has been tuned as 100 and T has been tuned as 500. While, all compared algorithms and IZOA have been run 20 times against twenty benchmark functions and CEC2019 independently. The hardware and software of the experiment is as follows:

The hardware is a windows 10 operating system PC with an Intel (R) core TM i5-8250U CPU @ 1.60 GHz and RAM 8GB of memory. The software of the experiment is MATLAB R2022b.

C. Test based on CEC2019

Table 2 shows the best (Best), average (Mean) and standard deviation (Std) of the results obtained by WOA, GWO, SABO, ZOA and IZOA for all functions in CEC2019. For F_1 and F_5 , IZOA obtains the best performance among five algorithms. For F_2 , the best solution and

An Improved Zebra Optimization Algorithm

anti-interference ability of IZOA are better than these of other algorithms. For F6 and F8, the best solution obtained by IZOA is much better than that of other algorithm and the stability of IZOA is greater than that of WOA, SABO and ZOA. For F7, among the five algorithms, IZOA obtained the best optimal solution and stability. For F9, the performance

of IZOA is equal to that of other algorithms. For F10, the anti-interference ability of IZOA is better than that of other algorithms. However, for F3 and F4, the results of IZOA are not ideal. Because Levy flight strategy is introduced into IZOA, which lead to an expanded search range in the late of the algorithm.

Table 2 Experimental results of WOA, GWO, SABO, ZOA and IZOA for all functions in CEC2019

Function	Values	WOA	GWO	SABO	ZOA	IZOA
F1	Best	480.2436	1	1	1	1
	Mean	2.67e+06	1.27e+04	1.0037	1.0794	1
	Std	7.92e+06	4.56e+04	0.0162	0.3551	2.64e-16
F2	Best	3.46e+03	48.3315	4.4366	4.2327	4.3159
	Mean	6.91e+03	329.9626	8.3607	5.2762	4.8215
	Std	2.54e+03	205.4587	6.6743	3.0059	0.2267
F3	Best	1.4818	1.0182	4.4887	1.1808	1.1968
	Mean	4.7064	2.6845	6.9094	1.6541	3.5796
	Std	2.1952	2.3189	0.9489	0.3146	1.6333
F4	Best	18.9273	4.2154	30.0767	13.0966	8.9602
	Mean	46.7651	13.0330	40.7789	22.7756	27.2257
	Std	16.7490	6.9616	9.3218	6.8695	9.3360
F5	Best	1.3632	1.2327	1.8032	1.3930	1.0417
	Mean	2.0131	1.4929	2.8251	2.6680	1.1201
	Std	0.3813	0.2397	0.6266	1.2172	0.0496
F6	Best	6.0604	1.1312	2.6751	2.6438	1.0962
	Mean	8.5890	2.1201	4.6235	5.2674	3.5197
	Std	1.4235	0.8083	1.4988	1.1761	1.4909
F7	Best	598.9103	239.4682	1.45e+03	360.6706	155.3965
	Mean	1.19e+03	640.8363	1.75e+03	664.4358	627.0112
	Std	327.1039	236.5580	134.0821	156.8630	216.6422
F8	Best	3.4611	2.3823	3.8038	3.3497	2.3689
	Mean	4.4791	3.5806	4.5352	3.8813	3.8912
	Std	0.3898	0.4900	0.2395	0.3794	0.5421
F9	Best	1.2054	1.0981	1.0688	1.0430	1.0507
	Mean	1.4308	1.1494	1.2683	1.2215	1.1651
	Std	0.1701	0.0429	0.0693	0.0963	0.0507
F10	Best	21.0062	21.2681	21.2382	6.9070	20.9484
	Mean	21.2000	21.3882	21.3902	18.7993	21.0973
	Std	0.1386	0.0629	0.0785	4.4931	0.0608

IV. CONCLUSIONS

In this paper, an improved ZOA(IZOA) is proposed. IZOA introduced three strategies to improve performance in the original ZOA. By introducing opposition-based learning technology, the diversity of population can be increased to avoid falling into local optimal solutions. AO is introduced to enhance the ability of searching the optimal solution at the initial stage of the algorithm. In the late stage of the algorithm, Levy flight strategy accelerates the convergence speed of IZOA and avoids falling into the local optimal solution. To verify the usefulness and effectiveness of IZOA, CEC2019 were used as references. By comparison, the performance of IZOA is superior to or approximately equal to that of ZOA, WOA, SABO and GWO, which proves the effectiveness and stability of IAO.

However, IZOA performs poorly in solving fixed-dimensional multimodal function problems. Therefore, IZOA cannot solve all types of problems. In the future, we will introduce more strategies to optimize the performance of the algorithm proposed in this paper and apply IZOA to a wider range of fields.

References

- [1] Trojovská, Eva, Mohammad Dehghani, and Pavel Trojovský. "Zebra optimization algorithm: A new bio-inspired optimization algorithm for solving optimization algorithm." *IEEE Access* 10 (2022): 49445-49473.
- [2] Abualigah, Laith, et al. "Aquila optimizer: a novel meta-heuristic optimization algorithm." *Computers & Industrial Engineering* 157 (2021): 107250.
- [3] Trojovský, Pavel, and Mohammad Dehghani. "Subtraction-average-based optimizer: a new swarm-inspired metaheuristic algorithm for solving optimization problems." *Biomimetics* 8.2 (2023): 149.
- [4] Mirjalili, S., and Lewis, A, "The whale optimization algorithm," *Advances in engineering software*, vol. 95, pp. 51-67, 2016.
- [5] Abdel-Basset, Mohamed, et al. "Nutcracker optimizer: A novel nature-inspired metaheuristic algorithm for global optimization and engineering design problems." *Knowledge-Based Systems* 262 (2023): 110248.
- [6] Abdel-Basset, Mohamed, et al. "Spider wasp optimizer: A novel meta-heuristic optimization algorithm." *Artificial Intelligence Review* 56.10 (2023):

- 11675-11738.
- [7] Abdel-Basset, Mohamed, et al. "Kepler optimization algorithm: A new metaheuristic algorithm inspired by Kepler's laws of planetary motion." *Knowledge-Based Systems* 268 (2023): 110454.
- [8] He, Wenmin, et al. "Improve zebra optimization algorithm with adaptive oscillation weight and golden sine operator." (2024).
- [9] Bui, Nguyen Duc Huy, and Thanh Long Duong. "An Improved Zebra Optimization Algorithm for Solving Transmission Expansion Planning Problem with Penetration of Renewable Energy Sources." *International Journal of Intelligent Engineering & Systems* 17.1 (2024).
- [10] Dama, Anand et al. "Enhancing the Zebra Optimization Algorithm with Chaotic Sinusoidal Map for Versatile Optimization." *Iraqi Journal For Computer Science and Mathematics* (2024): n. pag.
- [11] Mhmood, Ali H., Bashra Kadhim Oleiwi, and Amer B. Rakan. "Optimal Model Reference Lead Compensator Design for Electric Vehicle Speed Control Using Zebra Optimization Technique." *Jordan Journal of Mechanical & Industrial Engineering* 17.4 (2023).
- [12] Pazhanimuthu, C. et al. "Performance Analysis of Voltage Profile Improvement in AVR System using Zebra Optimization Algorithms based on PID Controller." *e-Prime - Advances in Electrical Engineering, Electronics and Energy* (2023): n. pag.
- [13] Alhammad, Sarah, et al. "Multilevel Threshold Image Segmentation of Brain Tumors Using Zebra Optimization Algorithm." (2024).
- [14] Elymany, Mahmoud M., Mohamed A. Enany, and Nadia A. Elsonbaty. "Hybrid optimized-ANFIS based MPPT for hybrid microgrid using zebra optimization algorithm and artificial gorilla troops optimizer." *Energy Conversion and Management* 299 (2024): 117809.
- [15] Zare, Peyman, et al. "Maiden application of zebra optimization algorithm for design PIDN-TIDF controller for frequency control in offshore fixed platforms microgrid in the presence of tidal energy." *2023 8th International Conference on Technology and Energy Management (ICTEM)*. IEEE, 2023.

Yuqi Liu, School of computer science and technology, Tiangong University, Tianjin, China.