

Improved Whale Optimization Algorithm Based on Chaos Strategy and Gaussian Mutation

Haining Zhang, Tao Tao, Hongshen Liu*

School of Computer Science & Technology, Anhui University of Technology, Ma'anshan 243032, China.

ABSTRACT

Aiming at the shortcomings of the basic whale optimization algorithm's slow convergence speed and easy to fall into local optimum, an improved whale optimization algorithm IGWOA is proposed, which uses the chaotic strategy to initialize the population, and the elite reverse learning strategy to increase the diversity of the population. factor and nonlinear convergence factor to speed up the global convergence; by adding an adaptive threshold, the global search capability is improved. Finally, the Gaussian mutation strategy is used to improve the convergence efficiency of the algorithm. Simulation experiments are carried out on 6 standard test functions, and the results show the effectiveness of the improved whale optimization algorithm.

Keywords

Whale Optimization Algorithm; Tent Chaos Map; Elite Reverse Learning; Adaptive Weights; Gaussian Mutation

1. Introduction

The whale optimization algorithm (WOA) [1] is a new swarm intelligence optimization algorithm proposed by Mirjalili of Griffith University in Australia in 2016. Its advantages are simple operation, few parameters to adjust and jump out of the local optima. At the same time, there are many shortcomings, easy to fall into the local optimum, slow convergence speed. Many scholars have made various improvements to these shortcomings. For example, the literature [2] introduced an adaptive strategy; Kaur et al. introduced the chaotic map into the whale algorithm [3] (CWOA) and introduced 10 different chaotic map formulas, among which Tent chaotic mapping has the best effect by comparison, but there is still a lot of room for improvement in convergence accuracy and convergence speed. Long Wen et al. proposed an improved whale algorithm (IWOA) based on nonlinear convergence factors to solve large-scale problems [4]

In view of the lack of WOA, this paper proposes an initial population based on Tent chaotic mapping combined with elite direction learning strategy, add adaptive weights, nonlinear convergence factors to improve the global search performance, increase the adaptive threshold, improve the probability of early search, and avoid falling into local extremum too early. At the same time, Gaussian mutation [5] was carried out on the optimal value to improve the convergence efficiency of the algorithm, and the effectiveness of the algorithm was demonstrated by six test functions.

2. Algorithm Improvement

2.1. Improved The Whale Optimization Algorithm

- Chaos Mapping and Elite Reverse Learning Strategies

ICBASE2022@3rd International Conference on Big Data & Artificial Intelligence & Software Engineering, October 21-23, 2022, Guangzhou, China

* Corresponding author: e-mail: 695073265@qq.com (Hongshen Liu*)



© 2022 Copyright for this paper by its authors.
Use permitted under Creative Commons License Attribution 4.0 International (CC BY 4.0).
CEUR Workshop Proceedings (CEUR-WS.org)

The more evenly the initialized population is distributed in the search space, the more beneficial it is to improve the optimization efficiency and solution accuracy of the algorithm. The chaotic sequence generated by Tent map has good distribution and randomness, which can be used to significantly improve the optimization performance of the algorithm. The Tent formula is:

$$X_{t+1} = \begin{cases} 2X_t, & X_t < 0.5 \\ 2(1 - X_t), & X_t \geq 0.5 \end{cases} \quad (1)$$

$$X = lb + (ub - lb)y \quad (2)$$

Among them: lb and ub are the lower and upper bounds of x, respectively.

- Elite Reverse Learning Strategies formula

$$S(i, j) = Y_{maxd} + Y_{mind} - Y_{id} \quad (3)$$

The basic steps are as follows:

1) Tent mapping initializes the population S, and selects the first N/2 individuals with better fitness as the elite population E

2) Find the reverse population OE of the elite population E

3) Combine the population S and the reverse population OE to obtain a new population $\{S \cup OE\}$, calculate the objective function value of the new population, and select the N individuals with the best fitness as the initial population.

- Nonlinear Convergence Factor and Adaptive Weights

In the original whale algorithm, the performance of global optimization and local exploration mainly depends on the value of A. The change of A is affected by the change of the convergence factor a, and the value of a decreases linearly from 2 to 0 as the iteration progresses. , the decreasing speed is the same in the whole algorithm, which leads to the decline of the overall optimization ability of the algorithm, and reduces the diversity and flexibility of the whale population. So to solve this problem, a decreasing nonlinear convergence factor is introduced. The specific expression is as follows:

$$a = (a_{final} - a_{initial}) - (a_{final} - a_{initial}) * ((1 - (T_{max} - t)/T_{max})^k) \quad (4)$$

Among them: t is the current number of iterations, T_{max} is the maximum number of iterations, a_{final} and $a_{initial}$ are the initial and final values of the control parameter a, respectively, and K is the nonlinear adjustment coefficient.

By using a nonlinear convergence factor, the performance of the algorithm is improved to a certain extent. However, when it comes to changing the strategy formula, the convergence factor alone cannot effectively balance global optimization and local search. To solve this problem, the adaptive weight is added at the time of change, and the formula is as follows:

$$W(t) = (W_{end} - W_{initial}) + 0.5 * ((T_{max} - t)/T_{max})^\varphi \quad (5)$$

Among them: t is the current number of iterations, T_{max} is the maximum number of iterations, $W_{initial}$ and W_{end} are the initial and final values of the control parameter w, respectively, and φ is a constant coefficient. In summary, the position update formula defined in this paper is defined as:

$$X(t + 1) = W(t) * X^*(t) - AD \quad (6)$$

$$X(t + 1) = W(t) * X^*(t) + D_p e^{bl} \cos(2\pi l) \quad (7)$$

$$X(t + 1) = W(t) * X_{rand} - AD \quad (8)$$

- Adaptive Threshold

The probability threshold p of the original algorithm is set as 0.5, and this equal probability predation mode will fall into the local optimum. Aiming at this problem, an adaptive threshold p' is proposed to balance the global optimization and local search capabilities:

$$P' = 1 - (t/T_{max})^\mu \quad (9)$$

Among them, μ is a constant variable. At the beginning of the iteration, $P > P'$, the algorithm selects

the spiral method to update the leader's position with high probability. The latter period decreases to 0 at a slow rate as the probability threshold decreases. By iterative adaptive threshold, the convergence accuracy of the algorithm is improved.

- Gaussian Mutation

In the basic whale algorithm, the group update strategy is to generate a new individual near the current optimal individual $X_{best}(t)$, which will cause other individuals in the group to move like the optimal individual, thus causing the group to lose diversity and fall into the local optimal value. The solution is to introduce mutation operations. In this paper, Gaussian mutation is used, and a certain probability p^* is used to perform Gaussian mutation operation on the current optimal solution $X_{best}(t)$:

$$X_{best}(t+1) = X_{best}(t)(1 + Gaussian(\sigma)) \quad (10)$$

Among them, $X_{best}(t+1)$ represents the position of the individual after mutation, and $Gaussian(\sigma)$ is a random variable that satisfies the Gaussian distribution. The global optimal position is updated as follows:

$$X_{best}(t+1) = \begin{cases} X_{best}(t+1), & otherwise \\ X_{best}(t), & f(X_{best}(t+1)) > f(X_{best}(t)) \text{ and } rand < p^* \end{cases} \quad (11)$$

Among them, $rand$ represents a random variable between $[0,1]$, p^* is the selection probability of survival of the fittest, and $f(x)$ is the fitness value of the individual. It can be seen from formula (11) that by performing mutation operation on the current global optimal solution $X_{best}(t)$, the population can evolve towards the optimal solution, and at the same time, the search efficiency of the algorithm can be effectively improved.

2.2. IGWOA Algorithm Process

In summary, the IGWOA algorithm process provided in this article:

The pseudo-code:

Begin

Initialization parameters, initialize the whale population based on Tent chaos and elite reverse learning strategy, and generate an initial population with good fitness.

While($t < t_{max}$) do

For $t=1$ to N do

Calculate A ; C ; calculate W according to formula (5); calculate p' according to formula (9)

If($p < p'$) do

If($|A| < 1$) do

According to formula (6) the whale moves towards the optimal solution

If($|A| \geq 1$) do

According to formula (8) whales move towards random individuals

Else if ($p \geq p'$) do

Repel prey with bubble net according to formula (7)

End if

End for

Record the optimal whale position, Gaussian mutation, generate $rand$, probability p^* , compare the individual fitness values, and determine whether to receive the position of the new whale after the mutation

$t=t+1$

End while

End

2.3. Simulation Experiments and Analysis

- Benchmark Function

In order to verify the performance of IGWOA, the whale optimization algorithm (CWOA), standard

Whale algorithm (WOA) and Gray Wolf algorithm (GWO) based on chaotic search strategy are simultaneously conducted 20 times of comparative experiments under the 6 benchmark test functions in Table 1. We selected F(1)-F(6), including F(1), F(2) a total of 2 unimodal functions and F(3, F(4), F(5), F(6) a total of 4 multimodal functions are tested, as shown in Table 1:

Table 1. Benchmark Function

Function	Search Area	Theoretical
<i>F(1), Sphere</i>	$[-100,100]^n$	0
<i>F(2), Schwefel 2.22</i>	$[-10,10]^n$	0
<i>F(3), Generalized Rastrgin</i>	$[-5.12,5.12]^n$	0
<i>F(4), Ackley</i>	$[-32,32]^n$	0
<i>F(5), Generalized Griewank</i>	$[-600,600]^n$	0
<i>F(6), Kowalik</i>	$[-5,5]^n$	0.0003075

- Parameter Setting and Analysis

The main parameters of each algorithm are shown in Table 2:

Table 2. Algorithm Parameter Settings

Algorithms	Parameter
IGWOA	$a_{\text{initial}} = 2; a_{\text{final}} = 0; w_{\text{initial}} = 0.8; w_{\text{end}} = 0.4; \mu = 2; \phi = 2; k = 2$
CWOA	$a_{\text{initial}} = 2; a_{\text{final}} = 0; w_{\text{initial}} = 0.9; w_{\text{final}} = 0.2;$
WOA	$a_{\text{max}} = 2; a_{\text{min}} = 0$
GWO	$a_{\text{max}} = 2; a_{\text{min}} = 0$

Results are shown in Table 3:

Table 3. Algorithm experiment results

Function	Algorithm	Optimal value	Worst value	Average value	Standard deviation
<i>F(1), Sphere</i>	IGWOA	0	0	0	0
	CWOA	0	0	0	0
	WOA	7.8E-190	1.4E-206	5.4E-191	0
	GWO	9.83E-84	6.97E-88	9.38E-85	2.38E-84
<i>F(2), Schwefel 2.22</i>	IGWOA	0	0	0	0
	CWOA	0	0	0	0
	WOA	1.2E-112	1.2E-122	9.9E-114	3.1E-113
	GWO	1.16E-48	7.41E-50	3.2E-49	2.86E-49
<i>F(3) Generalized Rastrgin</i>	IGWOA	0	0	0	0
	CWOA	0	0	0	0
	WOA	0	0	0	0
	GWO	0	0	0	0
<i>F(4) Ackley</i>	IGWOA	8.88E-16	8.88E-16	8.88E-16	2.02E-31
	CWOA	8.88E-16	8.88E-16	8.88E-16	2.02E-31
	WOA	7.99E-15	8.88E-16	4.8E-15	2.55E-15
	GWO	1.15E-14	7.99E-15	9.77E-15	1.82E-15

<i>F(5) Generalized Griewank</i>	<i>IGWOA</i>	0	0	0	0
	<i>CWOA</i>	0	0	0	0
	<i>WOA</i>	0.066589	0	0.003329	0.01489
	<i>GWO</i>	0	0	0	0
<i>F(6) Kowalik</i>	<i>IGWOA</i>	0.000393	0.000308	0.000329	1.98E-05
	<i>CWOA</i>	0.000431	0.000308	0.000331	3.09E-05
	<i>WOA</i>	0.001239	0.000308	0.000601	0.000351
	<i>GWO</i>	0.020363	0.000307	0.002313	0.006173

The unimodal function is usually used to evaluate the development ability of the function. In F(1), F(2), IGWOA found the optimal value of 0. The function curve in Figure 1 shows that IGWOA has the fastest convergence rate.

Multimodal functions are often used to evaluate the search ability of a function. IGWOA found the optimal value 0 on the F(3) and F(4) functions, and showed the optimal mean and standard value in the test of the F(4) F(6) function. Fig. 1 It is proved that the initial population adjusted by the chaotic strategy converges faster than the traditional algorithm at the beginning of all the convergence curves. By comparing the numerical value and the curve as a whole, the IGWOA algorithm has better optimization performance than the CWOA, WOA and GWO functions.

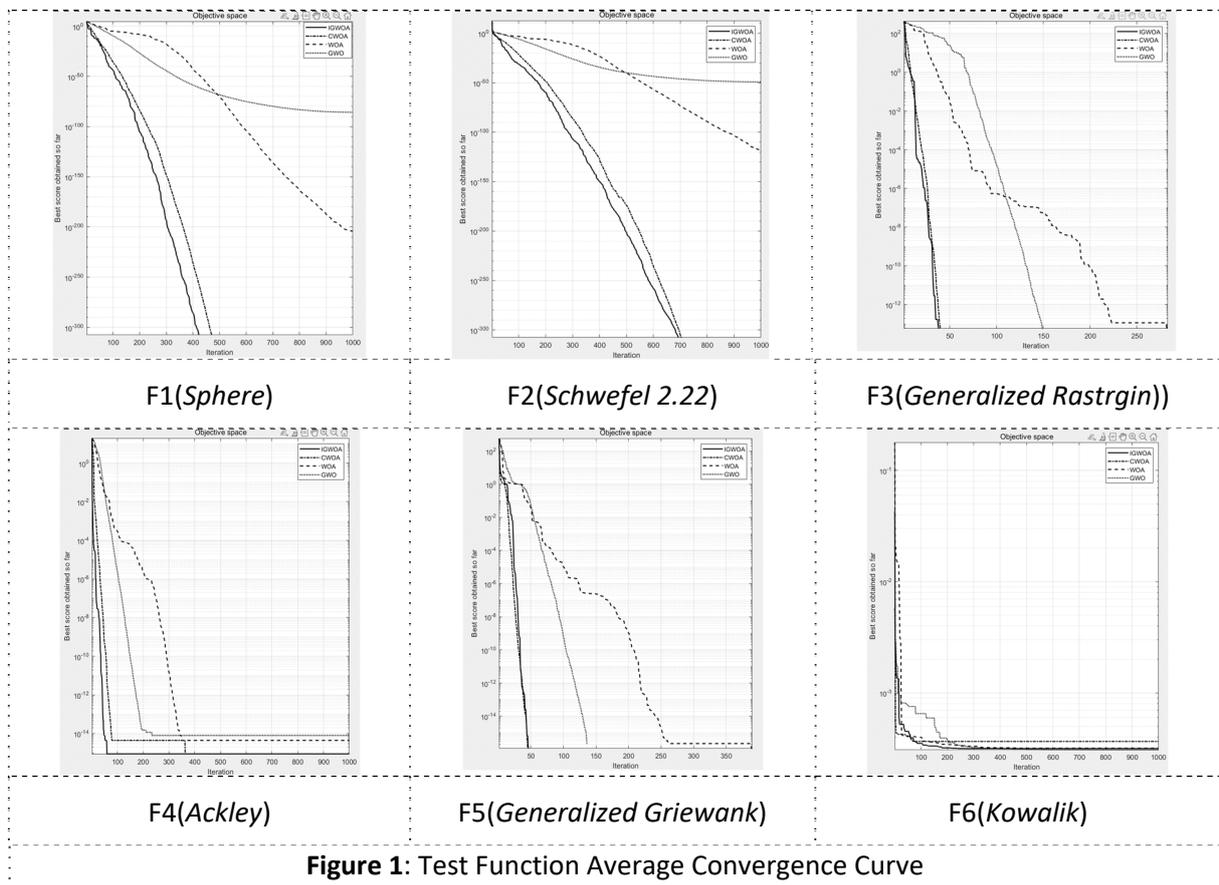


Figure 1: Test Function Average Convergence Curve

3. Conclusion

In order to improve the performance of WOA, this paper firstly uses chaos Tent mapping to initialize the population to make the population more uniform, then solves the fitness value, and uses the elite reverse learning strategy to obtain the initialization population with higher fitness value, which effectively improves the diversification of the initialization population. In the search and predation stage of the algorithm, nonlinear convergence factor and adaptive weight are added to improve the global

search ability of the population, so as to avoid the algorithm falling into the local optimal value too early. Moreover, by adding a custom threshold, the algorithm has a higher probability of searching prey in the early stage, so as to avoid falling into local extremum too early. Finally, Gaussian mutation is carried out on the optimal individual to accelerate the convergence performance of the algorithm and improve the local search ability to balance the global search and local search. Simulation results show that the improved algorithm in this paper has faster convergence speed and higher search accuracy.

4. References

- [1] Seyedali Mirjalili, Andrew Lewis. The Whale Optimization Algorithm[J]. *Advances in Engineering Software*, 2016, 95.
- [2] Guo Zhenzhou, Wang Ping, Ma Yunfeng, Wang Qi, Gong Changqing. Whale optimization algorithm based on adaptive weight and Cauchy variation [J]. *Microelectronics and Computer*, 2017, 34(09): 20-25 .DOI: 10.19304/j.cnki.issn1000-7180.2017.09.005.
- [3] Gaganpreet Kaur, Sankalp Arora. Chaotic whale optimization algorithm[J]. *Journal of Computational Design and Engineering*, 2018, 5(3).
- [4] Zhong Minghui, Long Wen. A Whale Optimization Algorithm for Randomly Adjusting Control Parameters [J]. *Science Technology and Engineering*, 2017, 17(12): 68-73.
- [5] Long Wen, Cai Shaohong, Jiao Jianjun, Tang Mingzhu, Wu Tiebin. An improved whale optimization algorithm for solving large-scale optimization problems [J]. *System Engineering Theory and Practice*, 2017, 37(11): 2983-2994.
- [6] Qu Liangdong, He Dengxu. Artificial Fish Swarm Algorithm Based on Adaptive Gaussian Mutation [J]. *Computer Engineering*, 2009, 35(15): 182-184+189.