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Network Intrusion Detection Algorithm based on Optimal Guidance B+ Tree

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Abstract. Aimed at the defect of slow convergence speed and easily running into local optimum of invasive weed optimization algorithm, a new improved algorithm of invasive weed optimization is proposed in the Paper. Based on the global guidance search strategy of improving artificial bee colony algorithm, the algorithm also combines backward learning idea, which not only enhances the development ability of algorithm but also improves the exploration ability of algorithm, besides, it avoids that algorithm runs into local optimum, thus improving the convergence speed of algorithm. At last, simulation verification is conducted on 5 standard testing functions of different dimensions and the test result shows: compared with GABC and standard IWO algorithm, the improved algorithm in the Paper has the advantage of relatively fast convergence speed and strong ability of jumping out of local optimum in function optimization aspect.

Key words. Free search algorithm, Guidance bee colony, B+ tree, Function optimization, Intrusion detection.

1. Introduction

Invasive Weed Optimization (IWO) is a new free search algorithm proposed by Mehrabian et al. [1] in 2006, of which a random model of weed invasion and growth is simulated, allowing the individual with better adaptability can be preserved through repeated iterations. Since the algorithm is robust, easy to implement and easy to operate, etc., it has been focused on and researched by many scholars once it was put forward, and has been well applied and developed in many fields [2–4]. However, as a cluster intelligent algorithm, standard IWO algorithm still has the problem of easily running into local optimum and slow convergence speed and low convergence precision in later period of development.

Aimed at above defects, literature [5] has proposed a hybrid IWO algorithm after combining with fast convergence speed of particle swarm optimization; literature [6] has introduced crossover operator to seed based on IWO algorithm, improving the diversity of population; literature [7] has introduced roulette mechanism to al-

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gorithm instead of survival competition operation; literature [8] has proposed an optimal search strategy to improve the low late convergence speed of algorithm. However, although above algorithms have improved the performance of algorithm to a certain extent, there are still problems in how to effectively avoid trapping into local optimum at the same time of improving the convergence speed of algorithm.

Aimed at the problem, a new improved algorithm of invasive weed optimization is proposed in the Paper. Based on the global guidance search strategy of improving artificial bee colony algorithm, the algorithm also combines backward learning idea, which not only enhances the development ability of algorithm but also effectively improves the exploration ability of algorithm, thus avoiding trapping in local optimum and improving the convergence speed of algorithm. A large number of simulation experimental results show the algorithm has relatively optimization efficiency and strong optimization performance.

2. Improved IWO algorithm

Through the process analysis of the standard IWO algorithm, it can be seen that the algorithm firstly uses the method of generating random numbers to produce weeds in the optimization process of breeding evolution, without taking the influence of population initialization on the diversity of population into account; in addition, since diffusion space is gradually reduced, it is still easy to trap into local optimum. Aimed at the above problems, the Paper firstly uses backward learning method to initialize IWO algorithm, at the same time, IWO algorithm is improved by combining with the relatively strong exploration ability of artificial bee colony algorithm's search strategy on nectar source, so as to better balance its development and exploration abilities, improve the convergence speed and search precision of algorithm.

2.1. Initialization of backward learning

In IWO algorithm, the method of generating random numbers is adopted to initialize the population without considering the influence of initialization on the diversity of population, which greatly influences the global search ability of algorithm. Therefore, assumed weed produces initialization position according to formula (1)

$$x_{i,j} = x_{\min,j} + rand \cdot (x_{\max,j} - x_{\min,j}) \,. \tag{1}$$

Where, $x$min, j and $x$max, j are the minimum and maximum of search space.

In literature [9], in researching bee colony algorithm, in order to improve the diversity of population, backward learning method is proposed to improve it. And by introducing the method, the Paper proposes a backward learning initialization method based on IWO algorithm, with details as follows:

1) Set population size $P = 1/4 \times$P_Max

2) {backward learning operation}

For $i = 1$ to P do

For $j = 1$ to D do
$Ox_{i,j} = x_{\min,j} + x_{\max,j} - x_{i,j}$
End ForEnd For3) Select P weeds as initial population from 2P weeds according to survival competence operation.

2.2. Global searching strategy of bee colony

Through the analysis on the process of IWO algorithm, it can be seen that in later development period of algorithm, due to the decreased diversity of population and reduced search space, algorithm is easily trapped in local optimum, while the algorithm has no strategy of jumping out of local optimum, which causes premature phenomenon easily.

Artificial bee colony algorithm [10] is a cluster intelligent optimization algorithm proposed by Karaboga. Due to the nectar source searching strategy of the algorithm, it has relatively strong exploration ability, and equation of nectar source searching can be seen in formula (2)

$$v_{i,j} = x_{i,j} + \varphi_{i,j}(x_{i,j} - x_{k,j})\,. \tag{2}$$

Where, $I,\ k = \{1, 2, \ldots, N\}$, and $i \neq k,\ j = \{1, 2, \ldots, D\}$. $\phi i,\ j$ is the random number between -1 and 1 (-1 and 1 are included). Seen from above formula, new candidate solution moves toward random individual in population, thus showing relatively strong randomness. However, the equation places emphasis on the exploration ability of algorithm and ignores the development ability of algorithm. Aimed at the problem, literature [11] proposes global optimum guidance strategy after combining with the search equation of particular swarm algorithm, namely

$$v_{i,j} = x_{i,j} + \varphi_{i,j}(x_{i,j} - x_{k,j}) + \psi_{i,j}(P_{g,j} - x_{i,j})\,. \tag{3}$$

Where, $Pg{,}j$is the global optimal solution, $\psi_{i,j}$ is the random number between 0 and 1.5 (0 and 1.5 are included. Through the strategy, the development and exploration abilities are effectively balanced.

Based on this, the Paper has combined with the global guidance nectar source searching strategy proposed in literature [11] to improve IWO algorithm, so as to improve the exploration ability of algorithm and avoid the premature phenomenon in algorithm; formula (4) is the global optimum guidance nectar source searching strategy of probability proposed based on literature [11]

$$\begin{cases} v_{i,j} = x_{i,j} + \varphi_{i,j}(x_{i,j} - x_{k,j}), & rand \leq 0.5\,, \\ v_{i,j} = x_{i,j} + \varphi_{i,j}(x_{i,j} - x_{k,j}) + \psi_{i,j}(P_{g,j} - x_{i,j}), & rand > 0.5\,. \end{cases} \tag{4}$$

2.3. Basic idea and steps of improved algorithm

Aimed at the problem that invasive weed optimization algorithm is easily premature and with relatively slow convergence speed in optimization process, the Paper has proposed the invasive weed optimization based on bee colony strategy

(IWOBCS), of which the basic idea is: at initial stage of IWO algorithm, backward learning initialization method is adopted to improve the diversity of population and enhance its global searching ability; in addition, after weed breeds seed at a certain proportion, global guidance nectar source searching strategy of artificial bee colony algorithm has been introduced to each seed probability, which avoids running into local optimum and improves convergence precision of algorithm at the same time. See detailed steps as follows:

1) Parameters for initialization algorithm
2) Use P weeds generated in search space by backward learning initialization to form initial population
3) The stop condition for while algorithm does not meet do
4) for $i = 1$ to P do
5) for $j = 1$ to D do
6) Calculate the number of bred seeds according to formula (1)
7) Calculate the standard deviation of seeds according to formula (2)
8) Produce seeds around each weed
9) end for
10) if $f(xi) < f(Pi)$ do
11) $Pi = xi$
12) end if
13) end for
14) for $i = 1$ to P do
15) for $j = 1$ to D do
16) Search new candidate solution vi according to formula (4)
17) if $f(vi) < f(Pi)$ do
18) $Pi = vi$, $xi = vi$
19) end if
20) end for
21) if $f(Pi)<\mathrm{f}(Pg)$
22) $\mathrm{Pg} = Pi$
23) end if
24) end for
25) end while
26) Output optimal solution

3. Simulation experiment

To test the effect of IWOBCS proposed in the Paper, the simulation contrast experiment under the conditions of 5 kinds of 30 dimensions and 60 dimensions with different standard test functions is carried out, where $f1\sim f2$ is unimodal function and $f3\sim f5$ is multimodal and 5 basic test functions have been given in Table 1. Given the number of initial weed as $P = 5$, P_Max $= 50$, $s\min = 0$, $s\max = 15$, $iter\max = 2000$, $\sigma initial = 3$ and$\sigma final = 0.00001$; the cluster size of GABC algorithm is 50 and Limit $= 100$ and the iterations of algorithm are all 2000 times. Meanwhile aimed at each test function, each algorithm is all randomly operated for 30 times and the optimal value, the worst value, mean value and variance are selected to inspect the searching performance of algorithm.

Table 1 is the comparison among mean value, variance, optimal value and the worst value after three algorithms of each function are optimized under different dimensions. It can be seen from the data in table 1 that when IWO algorithm and GABC algorithm are solving unimodal function problem, a better result can be got, while for the optimization of , it is difficult to get the satisfactory solution; however, IWOBCS algorithm proposed in the Paper has not effectively been combined with the development ability of IWO algorithm and the exploration ability of GABC algorithm, but no matter whether it is unimodal function or multimodal function, the optimal results are all superior to the other two algorithms. Meanwhile, it can be seen that on the optimization problem of multi-dimension function, the improved algorithm proposed in the Paper can perform better optimal performance.

To further verify the optimal performance of IWOBCS algorithm, three kinds of algorithm for convergence curve of 5 benchmark functions are respectively given in Fig.1 and Fig.5. It can be seen from Fig. 1 and Fig. 2 that because IWOBCS algorithm proposed in the Paper has adopted backward learning method to initialize the cluster and meanwhile adopted nectar source searching strategy with improved ABC algorithm, it makes the algorithm have faster convergence speed and meanwhile it can effectively avoid being caught in local optimum, so that the prematurity phenomenon appears; besides, it can be seen from Fig. 3 and Fig. 5 that compared with the other two algorithms, the algorithm improved in the Paper also has more significant strength on optimization problem of multimodal function. Table 1 Test result of 5 benchmark functions with different dimensions.

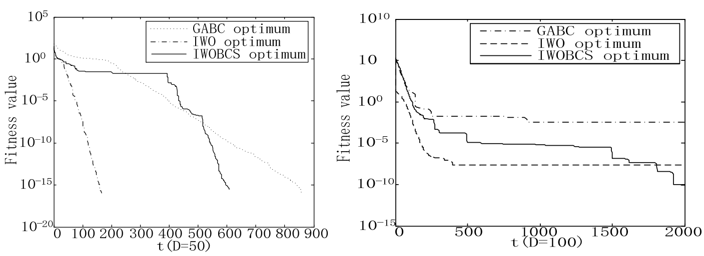

Fig. 1. Convergence curve of function $f1$

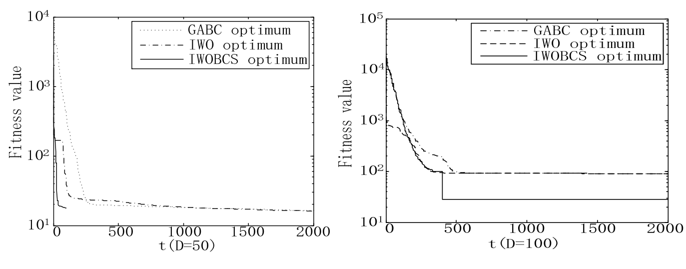

Fig. 2. Convergence curve of function $f2$

Table 1. Algorithm comparison

Function	Algorithm	Dimension	Mean	Deviation	Maximum	Minimum
$f1$	GABC	D = 50	3.13714E-015	1.97144E-021	6.79207E-015	0
	IWO		4.55572E-017	2.00306E-023	3.23074E-016	0
	IWOBCS		7.95155E-018	8.79213E-021	2.61564E-016	0
	GABC	D = 100	3.34037E-006	1.82907E-007	7.64184E-005	4.13668E-015
	IWO		5.6088E-010	1.45665E-009	8.65843E-007	1.87149E-012
	IWOBCS		8.15309E-016	3.32347E-016	9.89696E-014	4.72298E-018
$f2$	GABC	D = 50	12.58239	4.03788	25.65922	9.13687
	IWO		8.13687	3.64169	18.15703	6.12578
	IWOBCS		2.32635E-016	3.78719E-21	3.68434E-017	0
	GABC	D = 100	23.167895	7.458241	35.99033	21.724633
	IWO		19.56788	5.53871	28.25186	11.3074
	IWOBCS		1.21393	0.62695	3.25594	0.001534
$f3$	GABC	D = 50	9.18149	3.27583	12.90501	4.99201
	IWO		4.08007	1.89653	6.99267	1.44089
	IWOBCS		6,25426E-017	2.41953E-016	3.54952E-015	0
	GABC	D = 100	27.9554	8.89572	48.5578	17.75563
	IWO		18.4011	5.87342	31.20581	12.33147
	IWOBCS		16.72825	3.94662	28.54872	11.11022
$f4$	GABC	D = 50	3.5329E-016	3.84672E-015	3.48392E-013	2.48239E-018
	IWO		1.5325E-015	2.35425E-012	4.3825E-012	2.59472E-016
	IWOBCS		0	0	0	0
	GABC	D = 100	1.34235E-015	3.23921E-019	2.4523E-14	0
	IWO		4.2582E-008	2.83429E-009	3.4923E-07	3.4587E-010
	IWOBCS		2.35429E-017	1.39564E-021	4.2583E-017	0
$f5$	GABC	D = 50	1.3423E-012	2.4459E-013	4.2423E-011	1.2482E-015
	IWO		3.6849E-014	1.49823E-015	3.23211E-012	5.32534E-017
	IWOBCS		3.63284E-025	4.24532E-028	1.48349E-024	0
	GABC	D = 100	2.3939E-012	3.20185E-011	2.9528E-009	3.2382E-014
	IWO		5.23921E-014	1.28515E-013	3.3492E-012	5.2985E-015
	IWOBCS		3.23591E-017	3.8593E-016	7.39247E-016	2.39821E-017

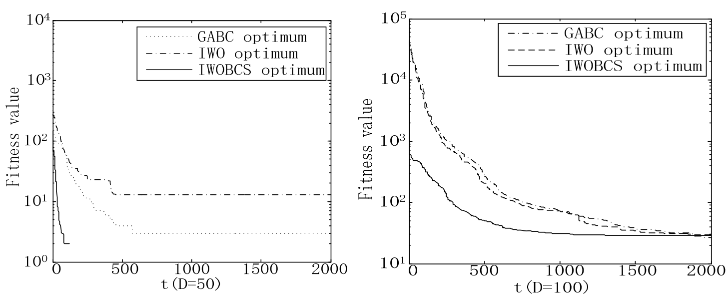

Fig. 3. Convergence curve of function $f3$

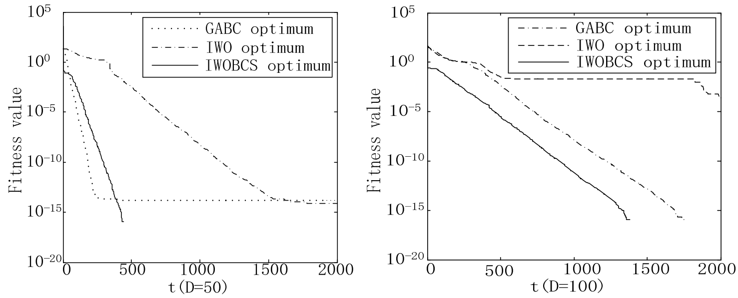

Fig. 4. Convergence curve of function $f4$

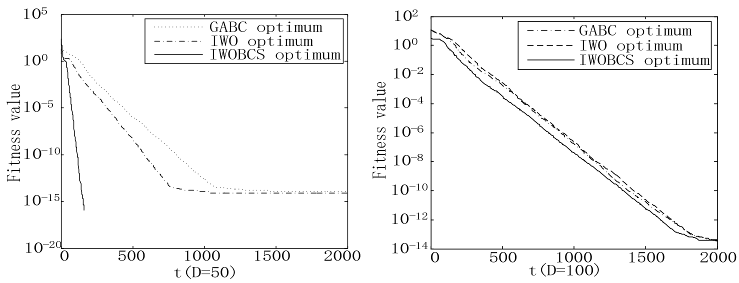

Fig. 5. Convergence curve of function $f5$

4. Conclusion

In order to prevent IWO algorithm from trapping in local optimum and improve its convergence precision and speed, the Paper has proposed IWOBCS algorithm. Since population diversity is the key factor of influencing the global searching ability of IWO algorithm, backward learning initialization method is introduced to improve population diversity in the Paper; at the same time, by referring to the strong exploration ability of artificial bee colony algorithm searching strategy, artificial bee colony algorithm is improved and then introduced into IWO algorithm in the Paper, which effectively improves the convergence speed and searching precision of algorithm. Aimed at the simulation of 5 benchmark functions, it shows that: compared with GABC algorithm and standard IWO algorithm, IWOBCS algorithm has much better optimization ability in the search space of 50 dimensions and 100 dimensions; however, how to improve IWOBCS algorithm's convergence precision in high-dimension function optimization at the same time of reducing complexity of algorithm is a subject needed to be further studied.

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References

[1] Ambusaidi M A, He X, Nanda P, et al.: (2016) *Building an intrusion detection system using a filter-based feature selection algorithm*[J]. IEEE Transactions on Computers, 2016:1-1.

[2] Shah B, H Trivedi B:(2012) *Artificial Neural Network based Intrusion Detection System: A Survey*[J]. International Journal of Computer Applications, 39(6):13-18.

[3] V. Brahmane A, Amune A:(2015) *An Efficient Approach for Dynamic Distributed Network Intrusion Detection using Online Adaboost-based Parameterized Methods*[J]. International Journal of Computer Applications, 117(18):7-13.

[4] Helali R G M: (2008) *Data Mining Based Network Intrusion Detection System: A Survey*[C]// Novel Algorithms and Techniques in Telecommunications and Networking, Proceedings of the 2008 International Conference on Telecommunications and NETWORKING. DBLP, 2008:501-505.

[5] Cavusoglu H, Mishra B, Raghunathan S: (2005) *The Value of Intrusion Detection Systems in Information Technology Security Architecture*[J]. Information Systems Research, 16(1):28-46.

[6] Patcha A, Park J M: (2006) *A Game Theoretic Formulation for Intrusion Detection in Mobile Ad Hoc Networks*[J]. International Journal of Network Security, 2(2):131-137.

[7] K. Santra A, Nagarajan S, V. N. J.: (2012) *Intrusion Detection in Wireless Networks using FUZZY Neural Networks and Dynamic Context-Aware Role based Access Control Security (DCARBAC)*[J]. International Journal of Computer Applications, 39(4):23-31.

[8] Álvaro Herrero, Corchado E, Pellicer M A, et al.: (2009) *MOVIH-IDS: A mobile-visualization hybrid intrusion detection system*[J]. Neurocomputing, 72(13-15):2775-2784.

[9] Ahmad I: (2005) *Feature Selection Using Particle Swarm Optimization in Intrusion Detection*[J]. International Journal of Distributed Sensor Networks, 151(3):41–49.

[10] Niu Y J, Zhao Y F: (2013) *Application of Improved LF Algorithm in Intrusion Detection*[J]. Computer & Modernization, 1(6):57-59.

[11] Stakhanova N, Basu S, Wong J: (2010) *On the symbiosis of specification-based and anomaly-based detection*[J]. Computers & Security,, 29(2):253-268.

[12] Chen M, Xin Y U: (2013) *A Tactical Datalink Wireless Intrusion Detection Method Based on an Evolutionary Neural Network*[J]. China New Telecommunications, 58(6):1285–1291.

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