Simulation of Web Page Big Data Capture Method Based on WNN Optimized by Locust Algorithm

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Abstract

In order to improve web page big data capturing ratio, the wavelet neural network (WNN) optimized by improved locust algorithm is established for capturing web page big data. First, the web page big data method is established, and the corresponding mathematical model is studied. Secondly, the neural network is established, and Legendre wavelet basis function is used as excitation function of hidden layer of WNN, and the theory models of input layer, output layer and hidden layer are constructed, and then the improved locust optimization algorithm is designed based on Levy flight local search strategy, linear decreasing parameter random jump strategy, decreasing coefficient update strategy and weight coefficient update strategy. Finally, a case study is carried out for validating the proposed web big data capturing method, results illustrate that the proposed method based on WNN optimized by improved locust algorithm can effectively improve web page big data capturing efficiency and accuracy, which has wide application view.

Keywords: Wavelet neural network, locust optimization algorithm, web page big data capture.

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1 Introduction

Recently the Internet industry has developed quickly, which has been applied in many fields. The data information has become main symbol, and the network has become the carrier of culture information, the network has become main means of information dissemination at this stage. The network has global and open characteristics, which provides opportunity for dissemination of malicious information to a certain degree. Therefore, for coping with this problem, the following research contents are listed as follows: the network data information should be controlled and supervised effectively, the harmful information should be intercepted quickly, and the bad data information should be prevented [1–3]. According to the existing research achievements, the search and mining of network big data has become a critical means to cope with these main research contents, and has been one of the most effective methods to find data information. The big data network concludes all kinds of information. It is critical to select an effective web page data capture method for searching and obtaining effective information quickly. The application of web search engines in current era can make network users to search in web pages and get required information according to key words or key sentences of data information needed [4, 5].

Similar data information of the same web site indicates that the HTML structure is similar, especially for a large number of information releases, they are usually generated using the same template or based on some dynamic web page technology. They are expressed in HTML format and have certain similarity. It describes the form of information, which is free, flexible and clear [6, 7]. The feature of Web big data capture is for web pages with similar HTML structure. The process of data capture is as follows: select the sample page, define the mode, generate rules, capture, remove redundant HTML, and store the data into the database for secondary sorting. The artificial neural network is an effective method for capturing web big data, which can improve speed and correctness of capturing web big data, which has wide application view. BP neural network is a frequently used method, which has applied in many fields, the stability of BP neural network is decided by parameters set, however this algorithm is prone to slow convergence and local minimum. In order to accelerate the convergence speed of the neural network and avoid the network falling into the local minimum, this paper establishes a web big data capture model using locust algorithm to optimize the parameters of WNN. Weights between each layer of the neural network and the expansion factor and translation factor of the wavelet basis function are the keys to determine the accuracy of the model. The traditional method uses gradient descent method to calculate these parameters, but the effect is not ideal. This paper uses locust optimization algorithm to optimize these parameters. Simulation results show that the WNN optimized by the locust algorithm has fewer iterations and higher accuracy. The optimized WNN is an feasible tool for coping with problems of Web big data capturing efficiency and accuracy [8–10].

2 Web Big Data Capture Method

Key feature capture of web big data is important part, the web page big data set is analyzed through local sample features, and the key information contained therein is captured. The ith feature of jth data sample is defined by C_{ij}, jth data sample is described by [11]

$$C_{ij} = [C_{j1}, C_{j2}, \ldots, C_{jj}]' \tag{1}$$

The critical feature capture process of web page big data is listed as follows:

The web page data sample is defined by $B \in R^{m\times n}$, the established data shortest neighbor graph $I_j = (W, F)$ is used to describe the partial composition of the data sample, where W represents node collection of web page, $W = B$, F represents the collection of connecting lines between nodes, the weighted matrix equation I_j is defined by $Q \in R^{m\times m}$, which is expressed by [12]

$$Q_{ij} = \begin{cases} e^{-\frac{\|b_i - b_j\|^2}{\eta}}, & if\ (b_i, b_j) \in F \\ 0, & else \end{cases} \tag{2}$$

where η represents the constant, Q denotes part of the intrinsic structure features in the web page data samples.

In order to capture the web big data information quickly and correctly, it is necessary to ensure that the numerical result of the function H_j is the smallest, and use H_j to describe the jth feature in the web page data, which is expressed by

$$H_j = \frac{\sum_{ij}(C_{ji} - C_{jk})^2 Q_{ij}}{J(C_j)} \tag{3}$$

where

$$\sum_{ij}(C_{ji} - C_{jk})^2 Q_{ij} = 2C_j' H C_j \tag{4}$$

$$J(C_j) = \sum_i (C_{ji} - \sigma_j)^2 D \tag{5}$$

where

$$\sigma_j = \frac{\sum_i C_{ji} D_{ii}}{\sum_i D_{ii}} \tag{6}$$

The following formula can be used to make the result of C_{ij} more accurate [13]:

$$C_j = C_j - \frac{F_j' D_1}{J' D_1} \tag{7}$$

The jth feature H_j can be obtained by

$$H_j = \frac{F_j' H F_j}{F_j' D F_j} \tag{8}$$

According to the calculation result of H_j, the minimum feature of it can be captured, that is, the main type of data in the web page.

Web page big data usually does not have obvious regularity and arrangement order, and has high complexity. This paper proposes a data capture method based on WNN optimized by locust algorithm. By capturing the main features, it realizes the classification and sorting of data and improves the efficiency of network search.

3 Basic Theory of WNN

Fourier transform is an integral transform, which can only be analyzed in time or frequency domains. The information in time domain and frequency domain in the signal can not be obtained, so it is more suitable for analyzing stationary signals. However, in the actual research work, the non-stationary signal is always processed. Because the time and frequency localization analysis should be implemented for the signal, the resolution of time is high at the high-frequency signal, the resolution of frequency is high at the low-frequency signal after the expansion and translation operation, therefore it can better capture any details of the signal. Compared with Fourier transform, wavelet transform has stronger ability to process unstable and abrupt signals [14].

The wavelet generating function $\varphi(t)$ must meet the allowable conditions:

$$\int_{-\infty}^{\infty} \frac{|\varphi(\eta)|}{|\eta|} d\eta < +\infty \tag{9}$$

Continuous wavelet expression is got by expansion and translation transformation of wavelet mother expression:

$$\varphi_{\alpha,\beta}(t) = |\alpha|^{-1/2} \varphi\left(\frac{t-\alpha}{\beta}\right) \tag{10}$$

where α represent scale factor, β represents translation factor.

For $g \in L^2(R)$, the continuous wavelet transform of signal $g(t)$ is expressed by [15]

$$V_g =< g, \varphi_{\alpha,\beta} >= |\alpha|^{-1/2} \int_{-\infty}^{\infty} g(t) \varphi_{\alpha,\beta} \left(\frac{t-\alpha}{\beta}\right) dt \tag{11}$$

Neural network are now widely used in various fields. Because of its strong fault tolerance, robustness and adaptive ability, which can effectively learn complex nonlinear relationships. WNN belongs to a feed forward neural network formed by combining wavelet transform and neural network theory. Compacting and loosing combinations belong to two means of connecting wavelet transform and conventional neural network at present. Compact combination can utilize wavelet transform as excitation of NN. At present, structure form of compact WNN is widely utilized in research work, and its ability to process data is stronger. The compact WNN is adopted in this paper, and its network topology is shown in Figure 1.

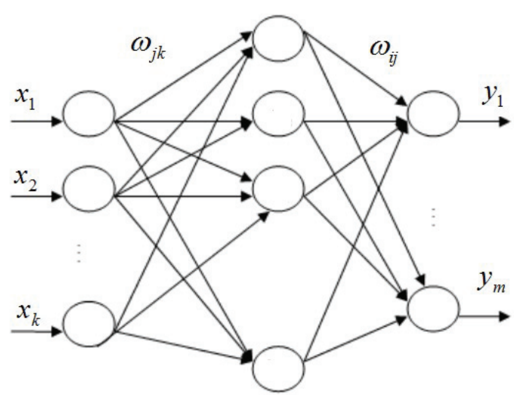

Figure 1 Diagram of WNN.

The WNN concludes input layer, output layer and hidden layer. Variables in input are $x_1, x_2, \ldots, x_k$, the variables in output are $y_1, y_2, \ldots, y_m$, the excitation function of traditional neural network is replaced by wavelet basis function. ω_{jk} represents input layer-hidden layer weight, ω_{ij} represents hidden-output layer weight, when input signal series is defined by x_i ($i = 1, 2, \ldots, k$), corresponding output of hidden layer is as follows [16]

$$H(j) = H_j\left(\frac{\sum_{i=1}^{k} \omega_{jk} x_k - \beta_j}{\alpha_j}\right),\ j = 1, 2, \ldots, l \tag{12}$$

where H_j illustrates wavelet basic function, α_j illustrates expansion coefficient, β_j illustrates translation coefficient. $H(j)$ illustrates output value of jth node in hidden layer.

Legendre wavelet is considered as basic function in this research, which is expressed by

$$\phi_{nm}(t) = \phi(k, \tilde{n}, m, t),\ k = 2, 3, \ldots,\ \tilde{n} = 2n - 1, n = 1, 2, \ldots, 2^{k-1} \tag{13}$$

where m represents Legendre polynomial order, t represents time. Legendre wavelet is defined on interval [0,1), which satisfies the following expression [17]

$$\phi_{nm}(t) = \begin{cases} 2^{k/2}\sqrt{m + \frac{1}{2}}L_m(2^k t - \tilde{n}), & \frac{\tilde{n} - 1}{2^k} \leq t < \frac{\tilde{n}+1}{2^k} \\ 0, & \text{other} \end{cases} \tag{14}$$

$L_m(t)$ represents m Legendre polynomial, which meets following conditions:

$$L_0(t) = 1,\ L_1(t) = t,\ L_{m+1}(t) = \frac{2m + 1}{m + 1} t L_m(t) - \frac{m}{m + 1} L_{m-1}(t) \tag{15}$$

Legendre wavelet set is an orthogonal set.

The computational formula of output is expressed by

$$y(i) = \sum_{j=1}^{l} \omega_{ij} H(j),\ i = 1, 2, \ldots, m \tag{16}$$

4 Training Algorithm Based on Improved Locust Algorithm

In order to improve the web big data capture effect of WNN, the improved locust optimization algorithm is applied to optimize parameters of WNN. The locust optimization algorithm (LOA) proposed in 2017, like the intelligent algorithm mentioned above, is also an intelligent optimization algorithm, which has been widely used at present. However, LOA is similar to the intelligent algorithm mentioned above. The algorithm itself has some problems, such as easy to fall into local optimization and insufficient convergence accuracy in the later stage. If it is directly used in the path planning of rice trans-planter, the defects of the algorithm will inevitably affect the effect of path planning. Therefore, it is necessary to improve the design of its defects in order to improve the effect of robot path planning. In this paper, LOA is used as the path planning method of rice trans-planter. At the same time, aiming at the defects of LOA, an improved locust optimization algorithm (ILOA) is proposed to improve the path planning effect of rice trans-planter.

LOA is an algorithm that simulates foraging behavior of locusts in nature. In the LOA, the position of the individual locust illustrates a candidate solution of optimization problem. It is mainly affected by three factors such as the interaction force between locust populations, wind force and gravity, and can be expressed by the mathematical model shown as [18].

$$X_i = S_i + G_i + A_i \tag{17}$$

where X_i is position of the ith locust; S_i is ith locust affected by the interaction between populations; G_i is the influence of external gravity on the ith locust; A_i is ith locust affected by the external wind.

When solving the mathematical optimization problem, in order to optimize the mathematical model, the external gravity influence G_i and wind influence A_i in Equation (17) are replaced with the location of target food T_d. In this way, Equation (17) can be rewritten into Equation (18).

$$X_i = S_i + T_d \tag{18}$$

where S_i is calculated by

$$S_i = \sum_{i=1, i \neq j}^{N} \frac{b_{\max} - b_{\min}}{2} s(d_{ij}) \vec{d_{ij}} \tag{19}$$

where $b_{\max}$ is the upper bound of search space, $b_{\min}$ illustrates lower bound of search space, d_{ij} illustrates distance between locust i and locust j; $\vec{d}_{ij}$ illustrates unit vector from location of locust i to location of locust j.

$$d_{ij} = |x_j - x_i| \tag{20}$$

$$\vec{d}_{ij} = \frac{x_j - x_i}{d_{ij}} \tag{21}$$

The s function in Equation (19) is a function for calculating the interaction force between locust populations, and its expression is shown as [19].

$$s(r) = fe^{-\frac{r}{l}} - e^{-r} \tag{22}$$

where f is attraction intensity parameter, r is attraction scale parameter.

Although Equation (18) is used to simulate the locust population, considering from the aspect of practical application, it is usually determined that the wind direction points to the target position without considering the gravitational factor. Therefore, finding the best individual position of the locust is to solve the optimization problem. The formula is as follows [20]

$$X_i^d = \eta \left\{ \sum_{j=1, j\neq i}^{N} \frac{\eta(b_{\max} - b_{\min})}{2} s(d_{ij}) \vec{d}_{ij} \right\} + \omega T_d \tag{23}$$

$$\eta = \eta_{\max} - t\left(\frac{\eta_{\max} - \eta_{\min}}{T}\right) \tag{24}$$

where T_d is the target position of locust colony, η is decline coefficient, ω is the weight coefficient, t is the current iteration times, $\eta_{\max}$ and $\eta_{\min}$ illustrate maximum and minimum values of decline factor.

In the whole search iteration process, the evaluation index of each locust position is fitness function (objective function). For the path planning of rice trans-planter, the most commonly used fitness function is to satisfy the shortest moving path. In the process of solving the optimization problem, Equation (18) is continuously used for cyclic iteration to obtain the optimal solution. The optimal fitness value obtained after each iteration is recorded as the currently obtained optimal solution. The location of the optimal solution is regarded as the location T_d of the target food until the maximal number of iterations is achieved.

The basic principle of the locust optimization algorithm shows that during the whole calculation process, the locust population has almost no change, lacks random factors, and has no mechanism to break away from local optimization, which makes algorithm easier to fall into the local optimization and cannot jump out, and ultimately affects the optimization performance. In order to improve optimization capability of LOA, LOA is enhanced based on following measures.

(1) Levy flight local search strategy

Levy flight strategy is a walking mode with strong randomness of moving step size, which can ensure that the probability of growing and short step size is roughly the same (the probability of short step size of Cauchy distribution is much greater than that of long step size). Levy flight random step size is introduced into the LOA algorithm. It can enhance the randomness and local searching capability of the algorithm, and improve probability of break away from local optimization. After the locust population completes an iterative search, the position of the individual locust is locally adjusted through Levy flight step, as shown as [21]

$$X = X + 10 \times s_{ts} \cdot L \cdot X \tag{25}$$

where L is the Levy flight step size, s_{ts} is a threshold function, which is used to control the flight method and change probability.

L is calculated by

$$L = \mu/|v|^{1/\beta} \tag{26}$$

where β ranges from 0 to 2, which is taken as 1.5 in this research; parameters μ and v serve normal distribution, the standard variances σ_μ and σ_v are calculated by

$$\sigma_\mu = \left\{ \frac{\Gamma(1+\beta)\sin(\pi\beta/2)}{\Gamma[(1+\beta)/2]2^{(\beta-1)/2}} \right\}^{1/\beta} \tag{27}$$

$$\sigma_v = 1 \tag{28}$$

s_{ts} is calculated by

$$s_{ts} = sign(x_{trans} - 1) + sign(x_{trans} + 1) \tag{29}$$

To a certain extent, Levy's flight guide provides a certain "vision" for the individual locust, which enables the individual locust to "see" the food in the area around him, so that the individual locust can conduct more targeted search in a local range.

(2) Linear decreasing parameter random jump strategy

In order to balance the search ability before and after LOA and have the mechanism of jumping out of local optimization, a random jumping out strategy with linear decreasing parameters is proposed. When the locust individual searches the position of the current optimal solution, the original position is replaced by the position. If the optimal solution is not found, the random jump out strategy is started, and its calculation method is shown as [22].

$$P_i = (2 - 2rand(0,1)) \cdot P_i \tag{30}$$

where P_i represents position of ith locust. Suppose a new P_i is found. If it is better, replace the old P_i. If it is replaced once, it can be considered that a jump out behavior has been successfully completed.

In order to ensure that the location information can be effectively used after the successful jump, the search iteration formula (18) is adjusted to formula (31):

$$P_i = S_i + (1 - q) \cdot T_d + q \cdot P_i \tag{31}$$

where q is control coordination parameters, the initial value of q is 0.

q is calculated by [23]

$$q = \begin{cases} q - 0.4, & \text{Not jump out and } q > 0 \\ 0, & \text{Not jump out and } q \leq 0 \\ 1.1, & \text{Jump out} \end{cases} \tag{32}$$

When the locust does not jump out or fails to jump out, q is still 0, which ensures that only S_i and T_d can affect the next iteration; When the locust individual has successfully jumped out once, q gradually decreases linearly to 0 in the following three iterations according to the interval of 0.35, which ensures that the locust individual can have an impact on the following three iterations after successfully jumping out of a local optimum.

(3) Decreasing coefficient update strategy

The parameter η can coordinate the global exploration and local development capabilities in the iterative process of the algorithm. However, it can be seen from Equation (22) that η decreases linearly with the increase of iteration times, which will slow down the convergence speed and easily fall into local optimization. Therefore the novel update strategy of decreasing coefficient is established, which is expressed by

$$\eta = \left[1 - \frac{1}{2}\left(\sin\left(\frac{\pi}{2}\sqrt{\frac{n}{N}}\right) + \cos\left(\frac{\pi}{2}\sqrt{\frac{n}{N}}\right)\right)\right] \cdot \left[\eta_{\max} - \frac{n(\eta_{\max} - \eta_{\min})}{N}\right] \tag{33}$$

where n illustrates current iteration times, N illustrates maximum iteration times, therefore the decline coefficient η can decrease at a faster rate in the early iteration of algorithm, so that the locust individual in the population can quickly approach the target, and enhance convergence speed of algorithm; In the late iteration of the algorithm, the decreasing speed of η slows down, so that individual can search the surrounding space carefully to avoid the algorithm falling into local optimization.

(4) Weight coefficient update strategy

The position update of locust individual depends not only on other individuals in the population, but also on the optimal solution in the current population. Therefore, the position of the optimal solution has an important impact on the movement of other individuals [24].

$$\omega = \frac{n}{N} \cdot \frac{\ln \omega_{\max}}{\ln \omega_{\min}} - \ln \omega_{\max} \tag{34}$$

where $\omega_{\max}$ illustrates maximum weight, $\omega_{\min}$ illustrates minimum weight.

5 Case Study

To validate precision and efficiency of proposed web page big data capture method based on WNN optimized by improved locust algorithm. The intranet of a certain university is selected as the simulation environment, and three computers are used in simulation analysis. The processor is a Pentium processor with a frequency of 45GHz, DDR2133 with a memory of 2GB, and the operating system of Windows10. At the same time, the three computers have separate network IP addresses. The transmission speed among the three nodes of the computer is set to 113MB/s, and the public broadband is connected to the 8MB/s network through the border router. In simulation experiment, the same 30 Web pages are chosen, and the parameters of improved locust

Table 1 Web page big data capture results

Parameter	1	2	3	4
Minimum	13	20	29	40
Maximum	80	102	123	146
Delay	4	5	6	7
Number of link	459	456	453	460
Capturing number of web page big data	496	385	378	365
Consuming time/s	12.5	13.4	14.3	15.4

Table 2 Web big data capturing results based on other methods

Parameter	BPNN-CA	RBFNN-PSA
Minimum	18	24
Maximum	93	115
Delay	9	11
Number of link	364	721
Capturing number of web page big data	316	237
Consuming time/s	17.4	19.2

algorithm are set as follows: The parameters of improved locust algorithm are listed as follows: $l = 2.0$, $f = 1.0$, $b_{\min} = 0.35$, $b_{\max} = 0.90$, $\eta_{\min} = 0.40$, $\eta_{\max} = 0.95$, the size of population is 350, the maximum iteration times is 400. The selected average value was obtained. The parameters in the computer system are set differently according to the methods proposed. The results of four big data captures are listed in Table 1.

In addition, the BPNN optimized by ant colony algorithm (BPNN-CA) and RBFNN optimized by particle swarm algorithm (RBFNN-PSA) are used to capture web big data with same parameters, and comparison results are shown in Table 2.

As seen from Tables 1 and 2, the capturing number of web page big data based on proposed in this research is more than that based on other two capturing methods, and the consuming time of proposed in this research is less than that of other methods. The proposed WNN optimized by improved locust algorithm can effectively improve capturing ratio of web page big data, and the capturing ratio is consistent with real situation.

The capturing ratio of different methods is shown in Figure 2, as seen from Figure 2, the average capturing ratio of proposed in this research is about 93%, and the average capturing ratio of BPNN-CA is about 76%,

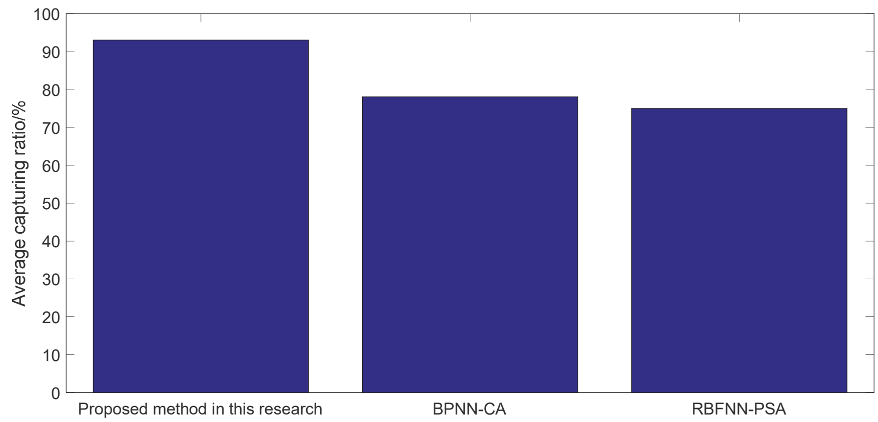

Figure 2

and the average capturing ratio of RBFNN-PSA is about 73%. Therefore the proposed research in this research can save capturing time and capture more web big data information, the calculation amount can reduce and the capturing ratio can be improved greatly.

6 Conclusions

In order to avoid the low efficiency and big error of traditional web page big data capturing method. The WNN optimized by improved locust algorithm is applied to capture web page big data. The whole web page collection is considered as big database, the perfect data information can be provide for monitoring and extracting, The feasibility and effectiveness of proposed in this research are validated through simulation analysis, results illustrate that the capturing number of web page big data based on proposed in this research is more than that based on other two capturing methods, and the consuming time of proposed in this research is less than that of other methods. The proposed WNN optimized by improved locust algorithm can effectively improve capturing ratio of web page big data, and the capturing ratio is consistent with real situation. In addition, the proposed research in this research can save capturing time and capture more web big data information, the calculation amount can reduce and the capturing ratio can be improved greatly. The future work concludes constructing novel WNN optimized by improved intelligent algorithm and establishing amended theoretical system.

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Biography

Zhao-yin Jiang received his Bachelor Degree in Computational Mathematics and Applied Software from Shandong Institute of Mining and Tecnology, China; and Master Degree in Computer Technology from Jiangsu University of Science and Technology. Currently he teaches in Yangzhou Polytechnic College and and presides over two provincial teaching projects. His research area mainly focuses on big data technology and data mining.