Application Research of Cuckoo Neural Network Algorithm in Surface Reconstruction

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Abstract: Aiming at the current BP neural network model for surface reconstruction, it is sensitive to the initial weight and threshold, easy to fall into the local minimum value, and the reconstruction accuracy is not high. The CS-BP surface reconstruction algorithm is proposed. Firstly, the cuckoo search algorithm is used to optimize the weight and threshold of BP model for the first time, and then the improved BP algorithm is used to further optimize, finally, the surface reconstruction model based on CS-BP neural network is established. Compared with the reconstruction results based on BP algorithm, quadratic fitting algorithm and Wolf neural network algorithm model, it is proved that the idea of using cuckoo algorithm to optimize BP model to construct surface reconstruction model is feasible, and cuckoo algorithm, like other swarm intelligence algorithms, can effectively improve the efficiency of BP surface reconstruction model.

1. Introduction

With the rapid development of computer science, modern advanced manufacturing technology and precision measurement technology, reverse engineering has become an emerging field of concern for scholars, and as the key technology of reverse engineering research, surface reconstruction technology has also attracted the attention of relevant scholars [1]. The traditional surface reconstruction is usually realized by parabola approximation or interpolation, but these methods are either of low precision or extremely difficult, so the practical application field is limited. With the rapid development of artificial intelligence technology and its wide application in various industrial fields, a number of scholars have used BP neural network to reconstruct the surface defect data [2,3], and achieved good data repair effect. Based on this, this paper mainly studied the surface reconstruction based on BP neural network.

However, because the initial weight and threshold of BP neural network is random, the global optimal solution cannot be obtained by the weight threshold parameters of BP model, which leads to the instability of calculation results and low calculation accuracy of the model. Therefore, a large number of improved methods for BP algorithms have emerged. The improved methods are generally divided into two categories. The first category is the improvement of BP neural network algorithm, such as the additional momentum method, the adaptive learning rate method with momentum item and the Levenberg-Marquard algorithm to improve the gradient descent algorithm [4]. The second type is to introduce a new intelligent algorithm to optimize the weight and threshold of BP neural network, and then improve the operation effect of BP neural network by combining with the improved BP algorithm to improve the operation efficiency of BP model[5]. This paper mainly studies the second kind of model, that is, the surface reconstruction model based on cuckoo BP neural network. The experimental results show that the model not only has higher reconstruction accuracy than BP neural network model, but also
has better operation stability, which is more valuable than BP neural network.

2. Model principles and implementation steps

2.1. Core ideas
Cuckoo Search (CS) algorithm, proposed by Yang and Deb in 2009, is an effective algorithm to solve optimization problems by simulating the parasitic breeding of some species of Cuckoo. At the same time, the algorithm also uses the relevant Levy flight search mechanism. Research shows that compared with genetic algorithm and particle swarm optimization, CS algorithm has the advantages of strong global search ability, fewer parameters and excellent search path, so it has a better balance between global search and local search, and the algorithm has good universality [6]. Therefore, based on the BP neural network surface reconstruction model, the cuckoo search algorithm is introduced into the optimization of BP model parameters. Firstly, the cuckoo algorithm was used to narrow the search scope of the weight threshold of BP model, and then the improved BP algorithm was used for the second search to determine the weight and threshold and form the final model.

2.2. Basic principles of CS algorithm
In order to simulate the parasitic breeding behavior of cuckoos, the CS algorithm assumes three rules, specifically [7]:

(1) cuckoos lay one egg at a time and incubate randomly in a nest, indicating a solution to the problem.
(2) choose the nest with the optimal egg in each generation, that is, the current optimal solution to the problem, and save the bird to the next generation.
(3) the number of nests is fixed, and the probability that the bird's egg is found by the host bird is Pa. Once a bird's nest is found, the host bird will discard the nest with the bird's egg and look for a new nest. Based on the above three rules, the pseudo-code of CS algorithm is as follows.

Initial population  \( x_i (i=1,2,\ldots,n) \)
Computational fitness  \( f_i \)

While (stop condition is not satisfied)

According to Levy Flight create a new  \( x_k \), calculate its  \( f_k \)
Randomly select a candidate solution  \( x_j \)
If (  \( f_k > f_j \) )  
  \( x_k \) replace  \( x_j \) 
End
Discarding the worse solution according to the Pa
Generate a new solution replace the discarded solution
Retain the best solution
End

2.3. CS-BP model algorithm steps
Step1 Model Structure Determination—BP neural network is a neural network that uses a back propagation algorithm. It usually contains an input layer, one or more hidden layers, and an output layer. For most problems, it is generally sufficient to choose an implicit layer to solve the problem. Therefore, the BP network model in this paper chooses a single hidden layer structure, and the basic structure of the model is shown in equation (1).

\[
Y = \text{purelin}[W2^{\ast}\text{tansig}(W1^{\ast}Pn + B1) + B2]
\] (1)

Where  \( Y \) is the output result,  \( W1, W2, B1, B2 \) are the BP model implicit layer and output layer weight and threshold respectively,  \( Pn \) is the input information, and tansig and purelin are the hidden layer and output layer activation functions respectively.

Step2 Nesting initialization—In this algorithm, the nest position represents a BP model weight threshold combination form, generally taking the value between [-1,1]. When the BP model structure is
determined, the number of weight thresholds is also determined, and the position dimension of the nest is also determined accordingly. Assuming that the number of nodes in the input layer, hidden layer, and output layer of the BP model are $innum$, $midnum$, and $outnum$, respectively, the position dimension of the nest is

$$M = midnum \times innum + outnum \times midnum + midnum + outnum.$$ 

After initializing the bird's nest, the bird population is initialized to $n$, respectively, and the probability $P_a$, the running accuracy, and the maximum number of iterations are found.

**Step 3** Fitness function determination - After completing the nest initialization, calculate the fitness value of the nest, and the calculation formula is as shown in equation (2).

$$\text{fitness} = \text{mse}(y_i - t_i) = \sum_{i=1}^{n} (y_i - t_i)^2$$  \hspace{1cm} (2)

Where $y_i$ is the expected output and $t_i$ is the actual output. The higher the fitness value, the better the nest position.

**Step 4** Location Update [8] - The traditional $i$-th bird's $t$-th iteration algorithm position $x_i^t$ is updated as shown in equation (3), where $\delta$ is the walk step and $\oplus$ is the point multiplication, $i = 1, 2, \cdots, n$. $L(\lambda)$ is a Levy random search path, obeying the Levy distribution, and is determined by equation (4).

$$x_i^{t+1} = x_i^t + \delta \oplus L(\lambda)$$ \hspace{1cm} (3)

$$L(\lambda) \sim \mu = \tau^{-\lambda}, (1 < \lambda \leq 3)$$ \hspace{1cm} (4)

In the actual calculation, because the integral operation efficiency of the Levy distribution is low, the Mantegana algorithm is generally used for the equivalent position update. Therefore, the position update formula adopted in this paper is as shown in (5), and the walk step is adjusted according to the formula (6). Obtain a new set of nest positions and calculate their fitness, where $stepsize_\alpha$ represents the the walk step control parameter, $step$ is the walk step, and $\alpha$ is the walk coefficient. Then compare with the position of the nest before the walk. If the new nest position is better than the position of the nest before the walk, update it, otherwise the update operation will not be performed.

$$x_i^{t+1} = x_i^t + stepsize_\alpha \oplus \text{randn()}$$ \hspace{1cm} (5)

$$stepsize_\alpha = \alpha \cdot step \oplus (x_i^t - x_{best})$$ \hspace{1cm} (6)

**Step 5** Comparison Selection - After the end of Step 4, a random number $r$ is generated, which is compared with the bird egg discovery probability $P_a$. If $r > P_a$, the formula (3) is used to change the position of the nest where the bird eggs are found, and a new nest position is obtained. The position of the new bird's nest is compared with the position of the nest before the discovery, and the parasitic nest in a better position is retained. If $r \leq P_a$, no location update is performed.

**Step 6** End the judgment - find out the optimal nest position in the nest after Step 5, and judge whether the test value meets the algorithm end condition. If it is satisfied, stop the search, output the optimal nest position, and decode the position parameter to give BP as the initial weight threshold parameter, the model waits for the improved algorithm to perform secondary optimization to determine the final model. Otherwise, return to Step 4 to continue the search.

### 3. Experiment and result analysis

#### 3.1. Sample parameter construction

In order to verify the effectiveness of the algorithm proposed in this paper, the necklace curve of example 1 shown in equation (7) and saddle surface of example 2 shown in equation (8) are respectively verified.

$$\begin{align*}
  x &= \sin(t) \\
  y &= \cos(t) \\
  z &= \sin(10y) + \sqrt{2 \sin(x)} - 0.5 \leq x \leq 0.5, -0.5 \leq y \leq 0.5
\end{align*}$$ \hspace{1cm} (7)

$$z = \frac{\sin(10y)}{\sqrt{2 + \sin(x)}}, -0.5 \leq x \leq 0.5, -0.5 \leq y \leq 0.5$$ \hspace{1cm} (8)

For example 1, take the step length as $\pi/100$ and generate 201 sample points composed of $[x, y, z]$. 
Take the first 150 as the training sample set and the last 51 as the test sample set.

For example 2, take 4 subintervals on the interval \( \{ (x, y) | -0.5 \leq x \leq 0.5, -0.5 \leq y \leq 0.5 \} \), 251 points for each subinterval, a total of 1004 points, so that 1004 sample points composed of \([x, y, z]\) are produced. Take the first 900 as the training sample set, and the last 104 as the test sample set.

### 3.2. training algorithm selection

The number of input layer nodes is \( \text{innum} \), and the node of output layer is \( \text{outnum} \). For the hidden layer node \( \text{midnum} \), this paper adopts the golden section search algorithm proposed by professor Kevin Xia [9], and uses the formula (9) to determine it as 7.

\[
\frac{(\text{innum} + \text{midnum})}{2} \leq \text{midnum} \leq (\text{innum} + \text{outnum}) + 10
\]  

(9)

After confirmed the model structure, the next need to determine is the model of the training function, a gradient descent method is commonly used now (traingd) additional momentum method (traingdm), with vector method (traingdx) algorithm with adaptive momentum item, set the same parameter, traingd,traingdm and traingdx algorithm running result is as shown in Fig.1, the curve can be seen in this picture, traingdx efficiency is highest, it runs in the same number of minimum error in training, so the selected BP model for traingdx training function.

![Fig.1.BP improved algorithm training results](image)

### 3.3. analysis of experimental results

Fig.2 shows the fitness change curve of the BP model optimized by the CS algorithm. It can be seen that the output error of the model decreases rapidly after the optimization by the CS algorithm. The CS-BP algorithm is compared with the WPA-BP, basic BP algorithm, and quadratic fitting algorithm surface reconstruction results. Table 1 shows the reconstruction error comparison based on different algorithms. It can be seen from the table that the BP model reconstruction after the optimization of the necklace curve of the example 1 is obviously better than the unoptimized BP model, and the CS-BP algorithm. The computational error of the reconstruction model is only 0.0017 larger than the reconstruction model of the WPA-BP algorithm, and the error is smaller than the basic BP algorithm reconstruction model and the quadratic fitting algorithm reconstruction model by 0.0478 and 0.3645, respectively. For the case 2, the CS-BP algorithm reconstruction model has the smallest error, which is 0.0047 less than the WPA-BP algorithm reconstruction model, which is smaller than the basic BP algorithm reconstruction model and the quadratic fitting algorithm reconstruction model error respectively 0.0291, 0.0122 From
the comparison of the reconstruction errors of the two examples, it can be seen that the introduction of
the cuckoo algorithm into the BP neural network to optimize its weight and threshold can effectively
improve the efficiency of BP neural network surface reconstruction like the wolf group algorithm.

Fig. 2. CS algorithm optimization BP model weight and threshold fitness curve

| algorithms Examples | Quadratic fitting | BP | WPA-BP | CS-BP |
|---------------------|-------------------|----|--------|-------|
| Necklace curve      | 0.3842            | 0.0675 | 0.0180 | 0.0197 |
| Saddle surface      | 0.0171            | 0.0340 | 0.0096 | 0.0049 |

4. Conclusion
This paper combines the global search ability of the cuckoo algorithm and the adaptive ability of the BP
neural network. A CS-BP surface reconstruction method based on the initial weight and threshold of the
cuckoo-optimized BP neural network is proposed. Experiments on specific examples show that this
method, like other cluster intelligent algorithms, can effectively solve the problem that the traditional
BP neural network surface reconstruction model is not accurate due to the randomness of the initial
weight and threshold, and the experimental results are also It shows that the reconstruction accuracy of
the method is better than BP algorithm and quadratic fitting algorithm for both curve and surface. It has
good research feasibility in surface reconstruction. Of course, the most important meaning of this article
is that it can provide a new research idea for surface reconstruction.

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