Application of Wolf Swarm Neural Network in Surface Reconstruction

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Abstract. Although the traditional BP neural network has strong nonlinear fitting ability, it has poor global search ability, slow convergence speed and easy to be trapped into local minimum value, etc. Based on this, a WPA-BP hybrid neural network surface reconstruction algorithm combining the Wolf pack algorithm and BP algorithm is proposed. WPA-BP hybrid algorithm has both the adaptive ability of BP algorithm and the global optimization ability of WPA algorithm, which can improve the existing problems of BP algorithm model. Compared with the reconstruction results based on BP algorithm and quadratic fitting algorithm, the surface reconstruction model using WPA-BP hybrid algorithm has higher reconstruction accuracy and smaller reconstruction error.

1. Introduction
With the rapid development of modern advanced precision measurement technology, manufacturing technology and computer technology, reverse engineering has become a research field that has attracted much attention. Surface reconstruction has been the focus of reverse engineering research and has attracted the attention of many scholars. The problem of surface reconstruction is essentially the problem of surface data fitting. Therefore, the research on surface reconstruction is the study of surface fitting problem. Traditional surface fitting methods include parabolic tangential extension, B-spline interpolation, and scattered point interpolation, but these methods have their own limitations. If the surface defect area is larger, the repairing precision cannot be guaranteed. When b-spline interpolation and scattered point interpolation are used to repair the surface, the repair precision is very high, but the solution of the surface equation is very complex, with a large amount of calculation and great difficulty [1]. With the rapid development and wide application of neural network technology in various industrial fields, some scholars have used BP neural network to fit surface defects, and achieved good results.

The BP neural network is used to reconstruct the surface, and the parameters representing the mapping relation of the surface are stored in the weight threshold of the BP neural network. This storage mode of full mapping makes the reconstruction model of the BP neural network have strong fault tolerance and adaptive ability. The model does not affect the overall performance due to the damage of some neurons, nor does it distort the output due to the noise pollution of the input signal, so it has good robustness [2]. Therefore, using BP neural network to model the surface scattered points will make the model not only have higher approximation accuracy, but also have certain smoothing and anti-noise performance. However, since the BP algorithm is based on the principle of gradient descent, there are problems such as weak global search ability, slow convergence rate, and it is also easy to fall into local minimum values. In order to solve these problems, the improved BP algorithm is often used to model, but the improved algorithm cannot solve the problem of the local minimum value caused by the random
value of the initial weight threshold. Therefore, the model optimization effect is limited. Based on the analysis of the characteristics of the cooperative hunting activities of the wolves, Wu Husheng proposed the Wolf Pack Algorithm (WPA) and verified the effectiveness of the algorithm [3]. Fan Bin achieved good results in the application of WPA-BP neural network to cable fault location in 2016 [4]. Based on this, the WPA-BP algorithm is applied to the surface reconstruction. The experimental results show that compared with the BP algorithm model and the quadratic fitting algorithm model, the WPA-BP algorithm is more accurate and less error-prone.

2. **WAP-BP algorithm principle**

2.1. **Basic Principles of the WAP Algorithm**

WAP algorithm is an intelligent algorithm derived from the population structure and hunting behavior of wolves in nature. Fig. 1 shows the hunting process model of wolves. In the model, wolves participating in hunting behaviors are given the roles of leader wolf, spy wolf and fierce wolf. The entire hunting activity was abstracted as three kinds of intelligent behaviors: wandering, summoning, and besieging. The leader Wolf directs the overall action of the wolf pack according to the perceived wolf pack information, the spy wolf is responsible for finding the prey and constantly approaching the prey, and the fierce wolf rapidly approaches the prey and captures the prey according to the command of the leader wolf. In the hunting process, the "winner is king" and "strong survival" update mechanism is adopted to update the leader wolf and the wolf pack [5]. The steps of WAP algorithm are as follows [6]:

![Fig.1. Wolf pack hunting process model](image)

**Step1 Algorithm initialization**—If the number of artificial wolves is \( N \) and the dimension of the space to be solved is \( D \), then the position \( X_i = (x_{i1}, x_{i2}, \cdots, x_{id}) \) of a wolf represents a solution satisfying the condition, where \( x_{id} \) represents the position of the \( i \)-th artificial wolf in the \( d \)-dimensional space, and its objective function is \( Y_i = f(X_i) \), \( Y_i \) indicates the concentration value of the prey perceived by the wolf, that is, fitness. In the initial search space, the wolf with the best fitness value is the first wolf, denoted as \( Y_{lead} \). At the same time, the maximum number of iterations \( k_{max} \), the spy wolf scale factor \( \alpha \), the maximum number of walks \( T_{max} \), the distance decision factor \( \sigma \), the step factor \( S \), and the update scale factor \( \beta \) are initialized.

**Step2 Spy wolf walk**—According to formula (1), the position is updated until the fitness value of a certain wolf is \( f(Y_i) > f(Y_{lead}) \). Then replace the leader wolf, go to Step3; Otherwise, the spy wolf continues to walk until it has reached the maximum walk number \( T_{max} \), turn to Step3.

\[
x_{id}^k = x_{id} + \sin(2\pi \times \frac{p}{h}) \times \text{step}^d
\]

**Step3 Fierce wolf running process**—According to formula (2), the position is updated. If the fitness value of a wolf is \( f(Y_i) > f(Y_{lead}) \) after the update, the leader wolf is replaced. Otherwise, the fierce wolf continues to attack until the distance from the prey is less than the determination distance \( d_{near} \), turn to Step4. The calculation of the determination distance \( d_{near} \) is as shown in the equation (3).

\[
x_{id}^{k+1} = x_{id}^k + \text{step}^d_k \times (g_{id}^k - x_{id}^k) / | g_{id}^k - x_{id}^k |
\]

Where \( g_{id}^k \) is the position of the head wolf in the \( k \)-th generation of wolves in the \( d \)-dimensional space.
The method runs faster in the \( d_{new} = 1/(D \times \sigma) \times \sum_{d=1}^{D} \max_{d} - \min_{d} \) \end{equation}

Where \( \sigma \) is the decision factor and \([\min_{d}, \max_{d}]\) is the range of values for the \( d \)-dimensional variable.

Step4: The process of beating the spy wolf and the fierce wolf—During the siege, when the wolf’s current position fitness is greater than the original position’s fitness, the position is updated according to equation (4), and the leader wolf is updated at the same time, otherwise the position remains unchanged.

\[ x_{a}^{k+1} = x_{a}^{k} + \lambda_{step} \times |G_{a}^{k} - x_{a}^{k}| \] \end{equation}

Where \( \lambda \) is a random number between [-1, 1]. The walk step is \( step_{s} \), the attack step is \( step_{a} \), and the siege step is \( step_{s} \), have the relationship shown in equation (5).

\[ step_{s} = step_{a} / 2 = step_{a} \times 2 = \max_{d} - \min_{d} / S \] \end{equation}

Step5: Wolf group update—In order to maintain the number of high-quality wolves in the wolves, while maintaining the diversity of the wolves, select the worst-fit \( R \) wolf to eliminate, randomly generate \( R \) new wolves. Here \( R \) is determined by \([N/(2\times\beta), N/\beta]\), and \( \beta \) is the update scale factor.

Step6: Iteration stop judgment—Whether the maximum number of iterations is reached \( k_{max} \) or the optimization accuracy meets the requirements. If it is reached, the output of the optimal solution is performed. Otherwise, go to Step2.

### 2.2. BP optimization target

The mathematical description of the BP neural network optimization process is shown in equation (6):

\[
\begin{align*}
\min E(w, v, \theta, r) &= \frac{1}{N} \sum_{i=1}^{N} (y_{i} - t_{i})^{2} \\
\text{s.t.} \ w \in R^{m \times p}, \ v \in R^{p \times n}, \ \theta \in R^{p}, \ r \in R^{n} 
\end{align*}
\] \end{equation}

The essence of this formula is a set of combinations \( w, v, \theta, r \) for the weight threshold of the \( m-p-n \) neural network with an output error of \( \min E(w, v, \theta, r) \), \( y_{i} \) is the actual output of the \( k \)-th sample, and \( t_{i} \) is the expected output of the \( k \)-th sample. The basic idea of the BP algorithm is to pass the output error \( E(w, v, \theta, r) \) back to the input layer layer by layer through the hidden layer in some way, and distribute the error \( E(w, v, \theta, r) \) to all the nodes of each layer, so as to obtain the error signals of the nodes of each layer. The weight threshold \( w, v, \theta, r \) of each node is corrected based on the signal. The BP algorithm uses the gradient descent method to solve the weight threshold \( w, v, \theta, r \). The method runs faster in the initial stage, but in the later stage of operation, the output error is close to the optimal value. At this time, the algorithm runs extremely slowly, and if the error surface is multidimensional space, the surface may fall into a local minimum point during the training process. The change from the point to the multi-direction will increase the error, which will result in the training not being able to escape this local minimum. The network convergence speed and generalization ability Weak [7].

In view of the possibility that the BP algorithm is trapped in local minimum values, in order to reduce this possibility, the WAP algorithm is introduced into the BP neural network weight threshold optimization, and the combination of the weight thresholds randomly initialized by the BP algorithm is used as a group of wolves. The initial solution, using equation (7) as the objective function of the wolf group algorithm, the corresponding \( F \) is the fitness value of the artificial wolf at this time.

\[
\begin{align*}
f(w, v, \theta, r) &= E(w, v, \theta, r) = \frac{1}{N} \sum_{i=1}^{N} (y_{i} - y'_{i})^{2} \\
\text{s.t.} \ w \in R^{m \times p}, \ v \in R^{p \times n}, \ \theta \in R^{p}, \ r \in R^{n} 
\end{align*}
\] \end{equation}

### 2.3. WAP-BP algorithm design

Step1: Determine the BP network structure, use the surface data to repeatedly train the BP model, adjust the number of neurons in the hidden layer, and finally determine the BP network structure.
Step2 The WPA algorithm parameters are initialized, and the spatial dimension $D = (m + n + 1) * p + n$ is calculated according to the $m-p-n$ neural network topology determined by Step1. The initial position $X_i$ of the $i$-th wolf containing the ownership value and the threshold is randomly generated as shown in equation (8).

$X_i = \{w_{i1}, w_{i2}, \ldots, w_{inp}, v_1, v_2, \ldots, v_p, \theta_1, \theta_2, \ldots, \theta_p, r_1, r_2, \ldots, r_n\}$ (8)

Step3 The randomly generated artificial wolf position is decoded into the initial threshold of BP neural network, and then the network is trained by the surface training data. The error of the training result and the expected result is taken as the odor concentration function value, that is, the individual wolf fitness value. (7) is shown.

Step4 The leader wolf, the spy wolf and the fierce wolf are determined according to the size of the prey odor concentration function $f(w, v, \theta, r)$. The head wolf, the wolf and the wolf perform their own hunting behaviors to iteratively update their hunting positions until the iteration termination condition is met.

Step5 The leader wolf position with the best fitness value is output, and it is used as the initial weight threshold of the BP neural network, and then the network is trained twice to output the surface reconstruction result.

3. Simulation experiment

3.1. parameter settings

In order to verify the effectiveness of the algorithm proposed in this paper, the necklace curve of example 1 shown in equation (9) and saddle surface of example 2 shown in equation (10) are respectively verified. Figure 2 and figure 3 are images of example 1 and example 2 respectively.

$$x = \sin(t), \quad y = \cos(t), \quad t \in (\pi, \pi) \quad (9);$$

$$z = \frac{\sin(10y)}{2 + \sin(x)}, -0.5 \leq x \leq 0.5, -0.5 \leq y \leq 0.5 \quad (10)$$

Fig.2. shows the necklace curve of example 1

Fig.3 shows the saddle surface of example 2

For the case 1, the step size is $a$, and a total of 201 sample points composed of $[x, y, z]$ are generated, and the first 150 are used as the training sample set, and the last 51 are used as the test sample set. The input layer node is composed of $x, y$, and the output layer node is $z$. For the hidden layer node, the golden section method [8] is determined by repeated calculation to be 7, so the basic structure of the BP model is shown in Fig.4.
For the second example, four sub-intervals are taken in the \( \{(x, y) | -0.5 \leq x \leq 0.5, -0.5 \leq y \leq 0.5\} \) interval, and each sub-interval takes 251 points, a total of 1004 points, thus producing 1004 sample points composed of \([x, y, z]\), taking the first 900 as a training sample set, the last 104 are used as test sample sets. Since the number of input layer nodes and output layer nodes is the same as in the first example, the BP structure model shown in Fig.4 is also employed.

### 3.2. experiment

The WPA-BP algorithm is compared with the basic BP algorithm and the quadratic fitting algorithm surface reconstruction results. Fig.5-7 is a reconstruction result graph of the three algorithms used in the example 1. The graph can be intuitively seen. Because the BP algorithm has the adaptive ability, the reconstruction curve is better than the quadratic fitting algorithm. The processing effect on local problems is better, and the reconstruction curve based on WPA-BP algorithm is the closest to the original curve shape. This shows that the model reconstruction is more accurate after further optimization of BP model parameters. Fig.8-10 is the reconstruction result graph of example 2 with three algorithms. It can be intuitively seen from the figure that the images generated locally by the three algorithms are different, and it is impossible to distinguish the quality of the images reconstructed by the three algorithms based on the images.
Fig.9. BP reconstructed surface  
Fig.10. WPA-BP reconstructed surface
In order to further compare the efficiency of the algorithm, the mean square error MSE is used to compare the efficiency of the algorithm reconstruction. Table 1 shows the reconstruction error comparison based on different algorithms. It can be seen from the table that the necklace curve has the largest error and the WPA-BP algorithm has the smallest error due to the large image bending in the reconstruction section and the poor reconstruction effect of the quadratic fitting algorithm. For example 2, since the reconstructed image is close to the quadratic fitting, and the BP algorithm is not sufficient to train local points during the training, the quadratic fitting reconstruction is better than the BP algorithm. For the reconstruction model based on WPA-BP algorithm, because WPA algorithm has strong global optimization ability, its optimization of weight threshold of BP algorithm makes the BP model get rid of the local optimization problem very well, so the reconstruction error of the reconstruction model based on WPA-BP algorithm is the minimum.

Table 1. reconstruction error comparison based on different algorithms

| Reconstruction algorithm       | Example 1 | Example 1 |
|-------------------------------|-----------|-----------|
| Quadratic fitting algorithm   | 0.3842    | 0.0171    |
| BP algorithm                  | 0.0675    | 0.0340    |
| WPA-BP algorithm              | 0.0180    | 0.0096    |

4. Conclusion
This paper combines the global search ability of wolf swarm optimization algorithm and the adaptive ability of BP neural network, and proposes a method of surface reconstruction based on the initial weight threshold of BP neural network based on wolf swarm optimization. This method has strong adaptive modeling ability, local fault tolerance ability and global approximation optimization ability. It can effectively solve the problem that traditional BP neural network is prone to fall into local minimum due to the randomness of initial weight threshold, and find the global optimal solution quickly and efficiently. Through the reconstruction experiments of necklace and saddle surfaces, it is proved that the reconstruction accuracy of this method is better than that of BP algorithm and reconstruction algorithm for both curves and surfaces. It has good feasibility in surface reconstruction. Of course, the most important significance of this paper is to provide a new research idea for surface reconstruction.

Acknowledgments
The authors are grateful to the scientific research projects of Inner Mongolia higher education institutions support under grant No. NJZY19260 and College-level Project of Ordos Institute of Technology support under grant No. KYYB2018011.

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