Application of BA-BP neural network in surface reconstruction

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Abstract: Aiming at the problems of current BP neural network model for surface reconstruction that are sensitive to the initial weights and thresholds, easy to fall into local minima, and the reconstruction accuracy is not high, a BA-BP surface reconstruction algorithm is proposed. The model weights and thresholds are optimized by bat algorithm for the first time, and then the BP algorithm is used to further optimize the weights and thresholds of model. Then, a surface reconstruction model based on the BA-BP neural network is established. By comparing with the reconstruction effect based on BP algorithm, quadratic fitting algorithm, wolf pack neural network algorithm and cuckoo neural network algorithm model, it proves that the idea of using bat algorithm to optimize BP model to construct surface reconstruction model is feasible. Bat algorithm, like other swarm intelligence algorithms, can effectively improve the efficiency of BP algorithm surface reconstruction model.

1. Introduction

Three dimensional modeling is the key link of reverse engineering, which is the basis of subsequent product manufacturing, rapid prototyping, engineering analysis and product redesign. With three-dimensional model, we can use the existing CAD / CAM / CAE technology to redesign and analyze products, and then produce products [1]. Therefore, the reconstruction of three-dimensional model is the most critical and complex link in the whole reverse engineering. The traditional three-dimensional model reconstruction generally uses the surface fitting method based on the basis function, which has a good reconstruction effect, but it is difficult to solve the reconstruction function, and some of them cannot solve the reconstruction function, so the practical application is limited. With the wide application of BP neural network in scientific and technological fields such as non-linear modeling [2], function approximation [3], such as using BP neural network instead of traditional fitting methods in surface reconstruction, the model can be compared With strong fault tolerance and association ability, problems that are difficult to solve for the surface reconstruction function will be effectively solved, which is more conducive to the practical solution of the surface reconstruction problem.

However, because BP neural network adopts gradient descent algorithm, its random selection of initial weights and thresholds make the model easily fall into local minimum and cannot get global optimal solution, which lead to the problem of low reconstruction accuracy of BP model. The bat algorithm (BA) is a new heuristic swarm intelligence algorithm proposed by Cambridge scholar Yang in 2010 [4]. Existing research has shown that the optimization of BP neural network weights and thresholds by bat algorithm can effectively improve the calculation accuracy of the neural network model. Therefore, this study combines the bat algorithm and the BP neural network algorithm to construct the BA-BP algorithm surface reconstruction model. The final experimental results show that
the surface reconstruction model based on BA-BP algorithm can effectively improve the calculation accuracy of the reconstructed surface.

2. Principle of correlation algorithm

2.1 Basic principle of bat algorithm

The basic principle of bat algorithm is to simulate the process that bats send out ultrasound, and then detect the location of prey, bypass obstacles and find habitat according to the echo received by the acoustic locator. The loudness of the sound wave emitted by bats can change with the distance to the prey. Bats can calculate the distance and orientation of the prey, distinguish the species of the prey and judge the moving speed of the prey by the time difference between sending and receiving the sound wave [5]. The specific implementation process is divided into two parts: global optimization and local search, which are carried out alternately until the optimal solution is reached [6].

**Step1** Global optimization-let the bat's predator space be d-dimensional. At the t-th iteration, the position and flight speed of bat i are \( X_i \) and \( V_i \), respectively, and the current global optimal position is \( X^* \). Then the position and flight speed of bat i at time \( t+1 \) are updated as follows [7]:

\[
f_i = f_{\text{min}} + (f_{\text{max}} - f_{\text{min}}) \beta \\
V_i^{t+1} = V_i^t + (X_i^t - X^*) f_i \\
X_i^{t+1} = X_i^t + V_i^{t+1}
\]

Where \( f_{\text{min}} \) and \( f_{\text{max}} \) are the minimum and maximum frequencies of sound waves emitted by bats respectively, and \( \beta \) is the uniform random number in [0,1]. In the initial setting, the frequency of each bat's transmitting sound wave is subject to the uniform random distribution of \( [f_{\text{min}}, f_{\text{max}}] \). That is to say, first obtain the respective frequency according to formula (1), then update the speed and position according to formulas (2) and (3).

**Step2** Local search-predator bat chooses an \( X_{\text{old}} \) from the global optimal solution, then randomly generates a new solution \( X_{\text{new}} \) around it according to formula (4):

\[
X_{\text{new}} = X_{\text{old}} + \varepsilon A'
\]

Where \( \varepsilon \) is the random number in [-1,1], and \( A' = \frac{A}{r} \) is the average loudness of all bats at the t-th iteration.

The update rule of loudness \( A' \) and rate \( r' \) of sound waves emitted by bats: Assume that as long as a bat finds a prey, it will gradually reduce the soundness of its sound waves and increase its sound wave emission rate [8]. In the BA algorithm, the loudness \( A' \) and rate \( r' \) of sound waves emitted by a bat are adjusted according to the following formulas (5) and (6): [9]:

\[
A'^{t+1} = \alpha A' \\
r'^{t+1} = r'[1 - \exp(-\gamma t)]
\]

Where \( r'' \) is the initial rate, \( \alpha \) and \( \gamma \) are constants, \( 0 < \alpha < 1, 0 < \gamma \).

2.2 The core idea of BA-BP algorithm

The position component of bat in BA is regarded as the combination of weights and thresholds \( X = \{ w, \nu, \theta, r \} \) of BP neural network. Each bat uniquely determines a set of weights and thresholds, i.e. corresponding to a BP neural network. During the optimization of the bat algorithm, the change of the two positions before and after the bat individual is the corresponding update of the weights and thresholds of the corresponding BP neural network model. The fitness function value is the only criterion to judge whether the two position changes of individual bats are better. Since the purpose of optimization is to select a more appropriate combination of weights and thresholds, the sum of the error squares between the actual output value of BP model and the expected output value is adopted as the fitness
function, as shown in equation (7). By updating the positions of several bats, the combination of the initial optimization weights and thresholds \( \{w, v, \theta, r\} \) of the BP neural network can be searched, and then the weights and thresholds obtained from the initial optimization are brought into the BP model for secondary training to obtain the final reconstructed model weights and thresholds to build the final reconstruction model.

\[
F(w, v, \theta, r) = E(w, v, \theta, r) = \frac{1}{N} \sum_{k=1}^{N} (y_k - y'_k)^2
\]

\[\text{s.t.} \quad w \in R^{m \times p}, \quad v \in R^{p \times n}, \quad \theta \in R^p, \quad r \in R^n\]

(7)

Where \( N \) is the number of training samples, \( y_k \) is the actual value of the sample, \( y'_k \) is the model output value, \( m \) is the number of BP model input layer nodes, \( n \) is the number of output layer nodes, and \( p \) is the number of hidden layer nodes.

2.3 Steps of BA-BP algorithm

**Step 1** Parameter initialization—it is assumed that the bat population size is \( m \), the bat individual acoustic velocity is \( r \), the acoustic loudness is \( A \), the bat acoustic frequency is \([f_{\text{mm}}, f_{\text{mm}}]\), the maximum number of iterations is \( N_{\text{max}} \), and the search accuracy is \( \varepsilon \). At the same time, the bat initial position \( X = \{w, v, \theta, r\} \) and velocity parameter \( V \) composed of weights and thresholds are initialized in the \( d \)-dimensional space composed of BP neural network structure parameters.

**Step 2** Iterative search—calculate the individual fitness value according to formula (7), update the bat’s sound wave frequency \( f_i \), speed \( V'_i \) and position \( X'_i \) according to formulas (1), (2) and (3), and generate a random number \( \text{rand}_i \). If \( \text{rand}_i > r'_i \), choose the optimal bat individual and obtain a new local solution \( X_{\text{new}} \) by random walk of (4). Generate a random number \( \text{rand}_2 > A'_i \) and the fitness \( \text{fitness}(X_{\text{new}}) \) of the bat at the new position is better than the optimal fitness \( \text{fitness}(X) \) of the current group, accept this new solution and update the bat sound \( A'_i \) and rate \( r'_i \).

**Step 3** Iterative evaluation—find out the bat individuals in the optimal predation position and the corresponding optimal position in the current bat population. Determine whether the maximum number of searches is reached or the preset search accuracy is met. If yes, go to **Step 4** for the next position conversion. Otherwise, go to **Step 2** and then search for the best individual.

**Step 4** Parameter generation—assign the optimal position corresponding solution obtained in **Step 3** to the neural network corresponding weights and thresholds, the new weights and thresholds parameters of BP model are trained twice. When the training is finished, the final surface reconstruction model of BP neural network is obtained. Fig.1 is a flowchart of the BA-BP algorithm.
3. Experiment and result analysis

3.1 Construction of model structural parameters

Surface reconstruction is ultimately the fitting of logarithmic data points. Therefore, in order to verify the effectiveness of BA-BP combined algorithm, necklace curve and saddle surface shown in equation (8) and equation (9) are respectively used as examples to verify the data fitting effect of BA-BP combined algorithm model. Fig.2 and Fig.3 show the images of necklace curve and saddle surface respectively.

\[
\begin{align*}
\begin{cases}
  x = \sin(t) \\
  y = \cos(t) \quad t \in (\pi, \pi) \\
  z = xy
\end{cases}
\end{align*}
\]  
(8)

\[
\begin{align*}
  z = \frac{\sin(10y)}{2 + \sin(x)} \quad -0.5 \leq x \leq 0.5, -0.5 \leq y \leq 0.5
\end{align*}
\]  
(9)
For example 1, set the step size as $\pi/100$, and generate a total of 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, 251 points for each subinterval, a total of 1004 points, so that 1004 sample points composed of $[x, y, z]$ are produced, the first 900 are taken as the training sample set, and the last 104 are taken as the test sample set.

The input layer node is composed of $x$ and $y$, the output layer node is $z$, and the hidden layer node is calculated as 7 by golden section method [10]. Therefore, the basic structure of BP model adopted in weights and thresholds optimization is shown in Fig.4.

3.2 Analysis of experimental results

Compare the surface reconstruction results of the BA-BP algorithm with CS-BP, WPA-BP, basic BP algorithm, and quadratic fitting algorithm. Table 1 shows the comparison of reconstruction errors based on different algorithms. It can be seen from the table that the reconstruction effect of the optimized BP model for necklace curve of example 1 is significantly better than that of the unoptimized BP model and the quadratic fitting model. Among all the optimization models, the BA-BP algorithm reconstruction model has the smallest calculation error, and the error value is in the order of $10^{-4}$. The calculation result is very good. For the saddle surface of Example 2, compared to CS and WPA, the optimization error of the BP surface reconstruction model optimized by the BA algorithm is larger, but the optimization efficiency of the model is still higher than the quadratic fitting algorithm and the unoptimized BP algorithm. Therefore, the bat algorithm is introduced to optimize the BP neural network weight threshold parameters, and constructing a BA-BP surface reconstruction model is meaningful to improve the reconstruction efficiency of the BP model.

| Examples          | Quadratic fitting | BP   | WPA-BP | CS-BP   | BA-BP   |
|-------------------|-------------------|------|--------|---------|---------|
| Necklace curve    | 0.3842            | 0.0675 | 0.0180 | 0.0197  | 6.3897e-04 |
| Saddle surface    | 0.0171            | 0.0340 | 0.0096 | 0.0049  | 0.0108  |
4. Conclusion
This study combines the global search ability of the bat algorithm and the adaptive ability of the BP neural network, and proposes a BA-BP neural network surface reconstruction method based on the bat algorithm to optimize the initial weight threshold of the BP neural network. This method can effectively solve the traditional BP neural network Problems caused by random selection of initial weight threshold. Through experiments on two examples, it is proved that this method, like other swarm intelligence algorithms, can effectively solve the problem that the model reconstruction accuracy of traditional BP neural network surface reconstruction model is not high due to the random selection of initial weight threshold.

At the same time, another important significance of this research is that it can provide a new research idea for the neural network surface reconstruction. The optimization of the BP neural network through different optimization algorithms can get a better surface reconstruction algorithm than the unoptimized neural network. The optimization algorithms have different reconstruction accuracy, but the gap is not large. If the reconstruction results of various optimization algorithms can be optimized and combined, better accuracy results may be obtained. In the next step, the combined optimization of the reconstruction results of many kinds of optimized neural networks will be studied in order to obtain the combined surface reconstruction model with higher reconstruction accuracy.

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