Research on Fast Evaluation Algorithm Based on Hopfield Neural Network

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Abstract

The fast evaluation algorithm based on Hopfield neural network (HNN) was presented to solve problems of multiple influencing factors, complex evaluation mechanism, inaccurate evaluation results and slow evaluation process in water quality evaluation. In storage of evaluation criteria information, this algorithm performed orthogonal and symmetric processing of information to guarantee accurate storage of information and steady operation of the network. After storage of the evaluation criteria, the connection weights of the network were determined and the actual measured data input into the HNN model, where such data were evaluated in a fast manner. In addition, the stability of this algorithm was verified, proving that this fast learning algorithm could ensure steady operation of HNN, which converged to the minimum. The fast learning algorithm avoided modular calculations currently applied in the existing algorithms, to greatly reduce the computation. As a result, only one iterative calculation would be needed to obtain the correct water quality evaluation results, which significantly enhanced the speed of water quality evaluation. At the same time, this algorithm accurately saved the evaluation criteria to ensure correctness of the final evaluation results. Finally, this algorithm was applied in surface water environmental quality evaluation and eutrophic water quality evaluation and compared with other algorithms, leading to the conclusion that this algorithm could evaluate water quality of different kinds in a fast and accurate manner.

Keywords: fast evaluation, Hopfield network, water quality.

1. INTRODUCTION

Social and economic development, especially development of industries, has severely contaminated water bodies, and then endangered human health. Severe water pollution will hamper sustainable development of the society and economy, in which case, protection of water environment has become an urgent task. In protection and treatment of the water environment, water quality evaluation is the most basic but the foremost section. Water quality evaluation is to analyze the general conditions of the water environment quality quantitatively. Accuracy of water quality evaluation has direct influence on implementation and effect of sewage treatment. In this sense, it will be of great significance to make correct evaluation on water quality.

The water environment system is a complicated, changing, and time-varying nonlinear system. Thus a proper evaluation model and method will be needed to correctly evaluate the water quality. In 1925, Streeter and Phepls(Rinaldi et al., 1979) proposed the earliest water quality model, which was a deterministic mathematical model that only considered BOD and DO and neglected the rest water quality parameters. Based on this model, new progress was made to add temperature as the state variable, so as to evaluate more complicated systems, but the number of water quality parameters considered was still too small. Subsequently, NOD, photosynthesis, settling and re-
suspension were added to the model, a breakthrough for the water quality evaluation model. In 1870s, the finite difference technology (Székely, 1998) was applied in calculations in the water quality model, to produce a high-dimension mathematical model. Along with progress of the high-dimension model, the water quality model developed from the single model to the comprehensive model boasting of higher reliability, predictability, comprehensiveness and scientificalness. Mathematical models, however, usually require a large number of hydrological parameters and water quality parameters that are mostly difficult to be obtained, which thus has restricted applicability and accuracy of the mathematical water quality models.

Traditional water quality evaluation methods include the single-index method, the synthetical index method, the fuzzy evaluation method and the grey theory method. The single-index method (Prati et al., 1971) applied one factor to evaluate the water quality and failed to reflect the overall situation of the water quality. The synthetical index method (Turner et al., 1981) applied mathematical operations based on the single factor, but it was subjective in weights matching of evaluation factors, which would directly influence the water quality evaluation results. With appearance of the fuzzy theory (Alkhatib et al., 2009), fuzzy mathematics was introduced to water quality evaluation. The fuzzy evaluation method (Gong and Jin, 2009) weighted the superstandard conditions of contaminations, but contamination and concentration were disproportionate, so this method was not always suitable for the practical situation. The grey theory method (Lee et al., 1997) treated water body as a gray system to determine the weights of pollutants according to the different water quality. This method avoided the defect in the fuzzy method that only one weight was used, but failed to consider particular damage caused by the superstandard pollutants, which would lead to less severe evaluation results. To sum up, the methods discussed above required artificial assumptions or settings, to produce strongly subjective evaluation results and thus brought about poor versatility of the model. Thus such methods can only work as reference in water quality evaluation. In 1880s, revival of neural network (Gazzaz et al., 2015; Khairi et al., 2016; Han and Qiao, 2014; Qiao and Han, 2012) created a new chance for the foundation of water quality model. The artificial neural network is a nonlinear system based on a large collection of neurons and has performed well in solving the nonlinear, uncertain and complex systems. It has provided an efficient method for water quality evaluation. To be specific, BP neural network (Singh et al., 2009) has already been employed in solving water quality evaluation problems. (Liu et al., 2008) applied BP neural network to lake water quality evaluation through building a classification model, proving that evaluation results from the BP neural network were objective and correct, provided that there were sufficient learning samples, or the evaluation results couldn't be accurate. (Lei and Liu, 2009) applied RBF neural network to the evaluation of lake eutrophication using the least square method for training the network, to produce objective and strongly universal evaluation results, but this method required a larger calculated amount. (Guo et al., 2002) applied the Hopfield neural network in water quality evaluation of the Yangtze valley, proving that this network could better evaluate the water quality, express the evaluation indicators quantitively and qualitatively, but its accuracy would fall with the increase in evaluation types. In addition, this method required multi-run of iteration, so the evaluation speed need improving further.

Hence, this paper has put forward a fast evaluation algorithm based Hopfield neural network. This algorithm adopts the matrix factorization method to perform orthogonal and symmetric processing of the stored information, to ensure correctness of information storage and stability of the network. This algorithm was applied to the surface water environmental quality evaluation and eutrophic water quality evaluation and proven to be valid and feasible. This paper is composed of the following sections: Section 1, introduction. Section 2, introduction of the Hopfield neural network model and implementation procedures. Section 3, design of the fast evaluation algorithm and verification of its stability. Section 4, taking the surface water environmental quality
evaluation and eutrophic water quality evaluation as example, the validity and feasibility of this algorithm were verified and comparison between this algorithm and other algorithms were made. Section 5, conclusions.

2. HOPFIELD MODEL

Hopfield neural network (Hopfield, 1984; Hopfield, 1982) is a form of single-layer recurrent artificial neural network popularized by Hopfield, with California Institute of Technology, in 1982. The recurrent network returns the output to the input. Under the effect of activation functions, the states of outputs of Hopfield neural network will change continually. When information is input, the network would generate output and return such output to the input, to produce continuous loop iteration. When the outputs change less and less until they reach the steady state, Hopfield neural network will produce a steady output.

The Hopfield neural network has a strong associative memory function. The earliest discrete Hopfield neural network output two values to represent the inhibition state and excitatory state of the neuron, respectively. The structure of Hopfield neural network is described taking the four neurons as example. Layer 0 is the network input, not actually the neurons and has no computation function. Layer 1 is the actual neuron layer to implement the cumulative sum of products of the input information and weights coefficient. Results of neurons are used to produce the ultimate output values with the activation function. The activation function is a threshold function, which means, when the neuron output is above the threshold, the neuron output will be 1 and when the neuron output is below the threshold, the neuron output will be -1. The network structure of the Hopfield neural network is shown in Fig.1.

For the discrete Hopfield neural network, the neuron outputs are produced by the cumulative sum of products of inputs and connection weights. Assuming the network input is \( y \), at time \( t \), the \( i \)th input of neuron can be expressed as \( y_i(t) \). Assuming the connection weight of the Hopfield neural network is \( w \), the connection weight between the \( i \)th neuron and the \( j \)th neuron will be \( w_{ij} \). The output \( e_i \) of the \( i \)th neuron at \( t \) can be obtained through computation, as below:

\[
e_i(t) = \sum_{j=1}^{n} w_{ij} y_j(t)
\]  

(1)
Where, \( n \) is the number of neurons in the Hopfield neural network.

Since the discrete Hopfield neural network is a two-value network and thus takes the threshold function as the activation function. When the neuron output is above the threshold, the final output of the neuron will be 1, while when the neuron output is below the threshold, the final output of the neuron will be -1. The threshold function \( f \) can be expressed as:

\[
  f(x) = \begin{cases} 
  1, & x \geq 0 \\
  -1, & x < 0 
  \end{cases}
\]  

(2)

The final output value of the neuron is produced by the activation function, namely the output of the \( i \)th neuron at \( t+1 \) is:

\[
  o_i(t+1) = f(e_i(t)) = f\left(\sum_{j=1}^{n} w_{ij}y_j(t)\right)
\]  

(3)

If the outputs of the Hopfield neural network have not reached the steady state, then the output \( o_i(t+1) \) herein will work as the network input for iteration operation according to equations (1-3) until the outputs reach the steady state.

The Hopfield neural network is composed of \( n \) neurons, so it will be complicated to compute the output of each neuron separately. To solve this problem, matrix can be adopted for calculation. Assuming the network input matrix is \( Y \), at \( t \), \( Y(t) \) can be expressed as:

\[
  Y(t) = [y_1(t), y_2(t), \ldots, y_n(t)]
\]  

(4)

The output \( O(t+1) \) of Hopfield neural network at \( t+1 \) can be obtained with the activation function:

\[
  O(t+1) = f(W.O(t))
\]  

(5)

Where, \( W \) is the connection weight matrix of the Hopfield neural network.

The final network output can be obtained through a number of iterations of the Hopfield neural network, however, provided that the network is steady and a suitable network connection weight matrix is available. Therefore, this paper has put forward a fast evaluation model and based on the Hopfield neural network, obtained a proper network connection weight through matrix factorization and accurately stored the stored information in the connection weights. The connection weight matrix obtained can fast calculate and process the input data and fast and accurately reach the steady state of the network.

3. FAST EVALUATION ALGORITHM

3.1 Design of the fast evaluation algorithm

The Hopfield neural network has a strong associative memory function to solve classification problems. Thus this paper has put forward a fast evaluation algorithm
Based on Hopfield neural network. The key point in the Hopfield neural network model is to determine the connection weights under the stable conditions.

Hopfield neural network stores information (namely the stable point) to the connection weights and gradually converges the network output to some stable point through network operations. Determination of the connection weights is critical. Currently methods used for determining the connection weights include the Hebb rule (Sompolinsky, 1987), outer product method (Yan et al., 2009) and orthogonal method (Amr and Salwa, 2013). But the Hebb rule is troubled with sample displacement and cross interference and is unable to guarantee precise memory for nonorthogonal samples. By contrast, the outer product method is easy to be implemented, but fails to produce ideal memory effect for samples strongly relevant to each other. The orthogonal method can guarantee convergence to the stable point and is widely used, but it has complicated computations, larger calculated amount and greater number of iterations in operation, and thus more time-consuming. Hence, this paper has put forward a fast algorithm to reduce number of iterations and calculation time with the prerequisite of guaranteeing convergence to the stable point.

Hopfield neural network stores the initial information to the network as the equilibrium points of the network. The network input will finally converge to some stable point. Assuming there are m pieces of information to be stored \( (I_1, I_2, \ldots, I_m) \), which will be used as training samples to be stored in the matrix \( S \), let

\[
S = [I_1^T, I_2^T, \ldots, I_m^T]
\]

It is learned from the orthogonal method that the pairwise orthogonal training samples are easier for storage and can work as stable point of the Hopfield neural network. Yet due to diversity of training samples, they are not always pairwise orthogonal, which is likely to cause inaccurate memory of samples. To avoid this problem, the matrix factorization method can be used to obtain the orthogonal training samples and accurately store the information, to ensure the network converges to the stable point. Thus, matrix factorization is made on equation (6), let

\[
S = UHV^T
\]

Where, \( U \) and \( V \) are two orthogonal matrices and \( H \) the pseudo-diagonal matrix.

Matrix factorization is used to obtain orthogonal matrix \( U \) and store relevant information in \( U \) for calculation of the network connection weights. This method guarantees accurate storage of samples and ensure convergence to the corresponding stable point.

The Hopfield neural network with symmetric connection weights is steady. To ensure network stability, its connection weights are designed to be symmetric. Set the diagonal matrix \( D \) and let

\[
d = \text{diag}[d_1, d_2, \ldots, d_n]
\]

Where, \( n \) is the number of neurons. \( d_i \) is the empirical value selected, herein being:

\[
\begin{align*}
d_i &= a_i & & 1 \leq a_i < 5 \\
d_i &= a_2 & & 0 \leq a_2 < 1, \quad i = 2, 3, \ldots, n
\end{align*}
\]

Thus we will obtain the network weight matrix:
It can be seen that the algorithm above can guarantee orthogonal properties of samples in the network so that the network can have stable convergence, and also avoid the modular computations in the orthogonal method, to greatly reduce the calculated amount and raise the network running speed. Therefore, this fast algorithm can effectively increase the speed of the network operation and guarantee accurate convergence to the stable point.

3.2 Stability analysis

In the dynamic system, the steady state means the energy function is gradually decreased until to the minimum value. The steady Hopfield neural network means the energy function of the network reaches the minimum value. The energy function of the Hopfield neural network is expressed as:

\[ E = -\frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} y_i(t) y_j(t) \]  

Thus, we can obtain:

\[ |E| \leq \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} |w_{ij}| |y_i(t)||y_j(t)| \]

\[ = \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} |w_{ij}| \]  

Thus it can be seen that the Hopfield neural network is bounded. The Hopfield neural network is realized through continuous evolution of the states of neurons. The network stability requires the energy function to be decreased gradually during the evolutionary process until to the minimum value. Thus variation in the energy function is as follows:

\[ \Delta E = E(t+1) - E(t) \]

\[ = -\frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} y_i(t+1) y_j(t+1) \]

\[ + \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} y_i(t) y_j(t) \]

\[ = -\frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} [y_i(t)+\Delta y_i(t)][y_j(t)+\Delta y_j(t)] \]

\[ + \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} y_i(t) y_j(t) \]

\[ = -\frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} [y_i(t)+\Delta y_i(t)+\Delta y_i(t)y_j(t)+\Delta y_i(t)\Delta y_j(t)] \]

\[ = -\Delta y_j(t) \left[ \sum_{i=1}^{n} w_{ij} y_i(t) \right] - \frac{1}{2} w_{ij} [\Delta y_j(t)]^2 \]  

Setting of the diagonal matrix in the fast evaluation algorithm has realized \( w_{ii} \geq 0 \), so \(-\frac{1}{2} w_{ij} (\Delta y_j(k))^2 \leq 0 \). Then discussion is made on \(-\Delta y_j(t) \left[ \sum_{i=1}^{n} w_{ij} y_i(t) \right] \):
1) If \( y_i(t)=y_i(t+1) \), then \( \Delta y_i(t)=0 \), namely \( \Delta E=0 \);

2) If \( y_i(t)=1, \ y_i(t+1)=-1 \), then \( \Delta y_i(t)=-2 \), namely \( \Delta E<0 \);

3) If \( y_i(t)=-1, \ y_i(t+1)=1 \), then \( \Delta y_i(t)=2 \), namely \( \Delta E<0 \).

It can be seen that the energy function changes \( \Delta E \leq 0 \) and is gradually decreased. At the same time, \( E \) is bounded, so the network always evolves to the direction that the energy function is decreased and will finally reach a stable point.

### 4. EXPERIMENT AND ANALYSIS

To verify validity and feasibility of the fast evaluation algorithm based on Hopfield neural network, the surface water environmental quality and eutrophic water quality were evaluated as example.

#### 4.1 Surface water quality evaluation

Surface water (Zhang et al., 2014) covers the dynamic and static water, liquid or solid, on the land surface, and is an important source for domestic water supply. The surface water environmental quality evaluation can indicate the law of variation and development of water environment quality, to provide basis for water environment system pollution control planning and environmental system engineering solution preparation. Only the correct evaluation on the water environment quality can guarantee the smooth going of the environment planning work. Thus, the surface water environmental quality evaluation is the foundation for integrated control of environmental pollution and a principle problem to be solved in improvement of the water environment quality.

Water quality evaluation shall be made according to the relevant standard. In Environmental quality standard for surface water (GB 3838--2002), water quality is divided into five classes according to the water area environment function and protected object of the surface water. Class I is applicable to source water and national nature reserves; class II to the centralized drinking water source class-I protected zones, rare aquatic life habitats, fish & shrimp spawning sites and juvenile fish nursery grounds; class III to the centralized drinking water source class-II protected zones, fish & shrimp wintering ground, migration pathway, aquiculture areas and the swimming areas; class IV to the general industrial water areas and recreational water regions where people have no direct contact; and class V is applicable to the agricultural water areas and the general landscape water areas. The Environmental quality standard for surface water has specified 109 standard items, with 24 basic items. In this study, the most important eight evaluation indicators have been selected.

<table>
<thead>
<tr>
<th>Indicator</th>
<th>I</th>
<th>II</th>
<th>III</th>
<th>IV</th>
<th>V</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dissolved oxygen (mg/l)</td>
<td>7.5</td>
<td>6</td>
<td>5</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td>Five day BOD (mg/l)</td>
<td>&lt;3</td>
<td>3</td>
<td>4</td>
<td>6</td>
<td>10</td>
</tr>
<tr>
<td>Chemical oxygen demand (mg/l)</td>
<td>&lt;15</td>
<td>15</td>
<td>20</td>
<td>30</td>
<td>40</td>
</tr>
<tr>
<td>Non-iron ammonia (mg/l)</td>
<td>0.02</td>
<td>0.02</td>
<td>0.02</td>
<td>0.2</td>
<td>0.2</td>
</tr>
<tr>
<td>Coliform group (number/l)</td>
<td>200</td>
<td>2000</td>
<td>10000</td>
<td>20000</td>
<td>40000</td>
</tr>
<tr>
<td>Volatile phenol (mg/l)</td>
<td>0.002</td>
<td>0.002</td>
<td>0.005</td>
<td>0.01</td>
<td>0.1</td>
</tr>
<tr>
<td>Fluorid (mg/l)</td>
<td>&lt;1.0</td>
<td>1.0</td>
<td>1.0</td>
<td>1.5</td>
<td>1.5</td>
</tr>
<tr>
<td>Cr(Ⅵ) (mg/l)</td>
<td>0.01</td>
<td>0.05</td>
<td>0.05</td>
<td>0.05</td>
<td>0.1</td>
</tr>
</tbody>
</table>
The information of the five standards in the *Environmental quality standard for surface water* was converted and stored into the matrix form. Taking class I in the standard as example, if criteria for class I were met, it was expressed with +1 and if not, with -1. To intuitively illustrate it, this study has converted the five classes into a graphic, as shown in Fig. 2. In Fig. 2, blue "●" indicates satisfaction of the classification criteria and green "●" indicates failure of meeting the classification criteria.

Evaluation criteria for the five classes were stored with the fast evaluation algorithm to determine the connection weights of the network. The test was conducted on the measured data of some monitoring point, as shown in Table 2.

![Figure 2. Environmental quality standard for surface water](image)

**Tabla 2 Measured data**

<table>
<thead>
<tr>
<th>Indicator</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dissolved oxygen (mg/l)</td>
<td>10.4</td>
<td>7.5</td>
<td>4.9</td>
<td>6.9</td>
<td>4.0</td>
</tr>
<tr>
<td>Five day BOD (mg/l)</td>
<td>1.2</td>
<td>0.7</td>
<td>6.3</td>
<td>1.6</td>
<td>3.0</td>
</tr>
<tr>
<td>Chemical oxygen demand (mg/l)</td>
<td>1.2</td>
<td>0.7</td>
<td>6.5</td>
<td>3.3</td>
<td>1.2</td>
</tr>
<tr>
<td>Non-iron ammonia (mg/l)</td>
<td>0.0005</td>
<td>0.0005</td>
<td>0.0005</td>
<td>0.0613</td>
<td>0.02</td>
</tr>
<tr>
<td>Coliform group (number/l)</td>
<td>2380</td>
<td>2000</td>
<td>5000</td>
<td>2380</td>
<td>2380</td>
</tr>
<tr>
<td>Volatile phenol (mg/l)</td>
<td>0.001</td>
<td>0.001</td>
<td>0.038</td>
<td>0.001</td>
<td>0.003</td>
</tr>
<tr>
<td>Fluorid (mg/l)</td>
<td>0.054</td>
<td>0.109</td>
<td>0.130</td>
<td>0.926</td>
<td>1.0</td>
</tr>
<tr>
<td>Cr(VI) (mg/l)</td>
<td>0.002</td>
<td>0.002</td>
<td>0.002</td>
<td>0.002</td>
<td>0.04</td>
</tr>
</tbody>
</table>

Five groups of measured data were taken as samples for testing, which were converted into the corresponding matrix form according to the evaluation criteria in Table 1 and then input into the Hopfield neural network model for evaluation. For intuitiveness, the graphic has been used to show the final evaluation results, as shown in Fig. 3. In Fig. 3, blue "●" indicates satisfaction of the classification criteria and green "●" indicates failure of meeting the classification criteria.
The evaluation results from the fast evaluation algorithm based on Hopfield neural network were compared with those from the BP algorithm and RBF algorithm, as shown in Table 3. Table 3 shows that water environment quality evaluation results obtained with the three algorithms are consistent, proving that the Hopfield neural network based fast evaluation algorithm can accurately store the evaluation criteria and correctly evaluate the surface water environment quality through the network running and evolution.

**Tabla 3** Comparison of evaluation results

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>BP</td>
<td>I</td>
<td>II</td>
<td>III</td>
<td>II</td>
<td>I</td>
</tr>
<tr>
<td>RBF</td>
<td>I</td>
<td>II</td>
<td>III</td>
<td>II</td>
<td>I</td>
</tr>
<tr>
<td>Fast HNN</td>
<td>I</td>
<td>II</td>
<td>III</td>
<td>II</td>
<td>I</td>
</tr>
</tbody>
</table>

Runtime of the three algorithms was contrasted, as shown in Fig. 4. Fig. 4 shows that BP algorithm requires the longest time, followed by RBF algorithm and the fast HNN, which agrees with the fact that BP algorithm has a more complicated operation process and larger calculated amount. This thus can prove that the Hopfield neural network fast evaluation method can greatly shorten the evaluation time.

The contrast test above has arrived at the conclusion that the fast evaluation algorithm based on Hopfield neural network can accurately and effectively evaluate the surface water environment quality and its runtime is far shorter than others. This algorithm is thereby proven to be feasible and valid.
4.2 Eutrophic water quality evaluation

Water body eutrophication is water quality pollution caused by excessive nitrogen and phosphorus in the water, which has caused proliferation of algae and other pelagic organisms, fall in the dissolve oxygen, deterioration of water quality and mass mortality of fishes and other organisms. Evaluation on the lake eutrophication is to precisely determine the nutrition status of water quality according to the indicators related to the nutrition status and their correlation.

Evaluation criteria for the eutrophic water quality include chlorophyll, total phosphorus, total nitrogen, COD and transparency. The eutrophic water quality is divided into 10 levels and three categories: oligotrophication, mesotrophication and eutrophication, with specific evaluation criteria shown in Table 4.

<table>
<thead>
<tr>
<th>Chlorophyll (μg/L)</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>4</th>
<th>10</th>
<th>26</th>
<th>64</th>
<th>160</th>
<th>400</th>
<th>1000</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total phosphorus (mg/L)</td>
<td>0.001</td>
<td>0.004</td>
<td>0.01</td>
<td>0.025</td>
<td>0.05</td>
<td>0.1</td>
<td>0.2</td>
<td>0.6</td>
<td>0.9</td>
<td>1.3</td>
</tr>
<tr>
<td>Total nitrogen (mg/L)</td>
<td>0.02</td>
<td>0.05</td>
<td>0.1</td>
<td>0.3</td>
<td>0.5</td>
<td>1</td>
<td>2</td>
<td>6</td>
<td>9</td>
<td>16</td>
</tr>
<tr>
<td>COD (mg/L)</td>
<td>0.15</td>
<td>0.4</td>
<td>1</td>
<td>2</td>
<td>4</td>
<td>8</td>
<td>10</td>
<td>25</td>
<td>40</td>
<td>60</td>
</tr>
<tr>
<td>Transparency (m)</td>
<td>1.5</td>
<td>1.3</td>
<td>1.1</td>
<td>0.9</td>
<td>0.7</td>
<td>0.5</td>
<td>0.4</td>
<td>0.3</td>
<td>0.2</td>
<td>0.12</td>
</tr>
<tr>
<td>Category</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
<td>8</td>
<td>9</td>
<td>10</td>
</tr>
<tr>
<td>Degree</td>
<td>Oligotrophication</td>
<td>Mesotrophication</td>
<td>Eutrophication</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The evaluation criteria for eutrophication were converted into the matrix form and stored in the connection weights with the fast evaluation algorithm. The evaluation criteria for the 10 classes would become the 10 stable points of the network. When test samples were input, the iteration operation of the Hopfield neural network would converge to some stable point. The five groups of measured data of some monitoring point were taken as test samples to verify the classification effect of the fast evaluation algorithm, as shown in Table 5.

<table>
<thead>
<tr>
<th>Data</th>
<th>Chlorophyll (μg/L)</th>
<th>Total phosphorus (mg/L)</th>
<th>Total nitrogen (mg/L)</th>
<th>COD(mg/L)</th>
<th>Transparency (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
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<td>42</td>
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<tr>
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<td>0.01</td>
<td>0.09</td>
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<tr>
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<td>0.9</td>
<td>1.8</td>
<td>1.1</td>
</tr>
<tr>
<td>4</td>
<td>15</td>
<td>0.05</td>
<td>0.3</td>
<td>1</td>
<td>0.8</td>
</tr>
<tr>
<td>5</td>
<td>61</td>
<td>0.18</td>
<td>6.2</td>
<td>3.9</td>
<td>0.5</td>
</tr>
</tbody>
</table>

The five groups of measured data were converted into the matrix form and input into the Hopfield neural network and gradually converged to some stable point through network operation, to finish evaluation on the test data. Evaluation results were classified to compare with those from the BP algorithm, as shown in Table 6. Table 6 shows that
evaluation results from the fast evaluation algorithm based on Hopfield neural network were consistent with those from the BP neural network, proving that the fast algorithm is accurate and can effectively and accurately store the evaluation criteria.

###Tabla 6 Contrast of classification results

<table>
<thead>
<tr>
<th>Data</th>
<th>Fast HNN algorithm</th>
<th>BP algorithm</th>
<th>RBF algorithm</th>
<th>Results</th>
</tr>
</thead>
<tbody>
<tr>
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<td>9</td>
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<td>2</td>
<td>2</td>
<td>2</td>
<td>Oilgotrophication</td>
</tr>
<tr>
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<td>4</td>
<td>4</td>
<td>4</td>
<td>Mesotrophication</td>
</tr>
<tr>
<td>4</td>
<td>5</td>
<td>5</td>
<td>5</td>
<td>Mesotrophication</td>
</tr>
<tr>
<td>5</td>
<td>7</td>
<td>7</td>
<td>7</td>
<td>Eutrophication</td>
</tr>
</tbody>
</table>

At the same time, the runtime of the two algorithms was contrasted, as shown in Fig. 5. The figure shows that the fast evaluation algorithm based on Hopfield neural network has taken a far shorter time than BP algorithm and RBF algorithm, proving fast speed of the fast HNN algorithm.

![Figure 5. Runtime of each algorithm](image)

It can be seen that the fast evaluation algorithm based on Hopfield neural network can accurately evaluate the eutrophic water quality and greatly shorten the evaluation time and enhance evaluation speed. Evaluation on the eutrophic water quality can prove validity and feasibility of the fast HNN algorithm.

###5. CONCLUSIONS

This paper has proposed a fast evaluation algorithm based on Hopfield neural network, which can accurately and fast evaluate water quality of different kinds and solve existing problems in current evaluation methods. This algorithm has adopted the matrix factorization to build orthogonal matrices, to guarantee symmetry of the network and thereby to ensure the network can accurately store information and run steadily. Evaluation on the surface water environment quality and lake eutrophication water quality has verified validity and feasibility of this algorithm. Contrast with other algorithms has led to the following conclusions:
(1) This algorithm has adopted the matrix factorization to design connection weight of the network so that information can be stored accurately and the network can be guaranteed to finally converge to a stable point.

(2) In design of the connection weight, this algorithm has avoided the partitioned operations of other algorithms, to greatly reduce the calculated amount and increase the evaluation speed.

(3) This algorithm can accurately and effectively evaluate water quality of different kinds. In this paper, two kinds of water quality were used to verify the validity and feasibility of this algorithm.

6. REFERENCES


