ESR temperature compensation algorithm based on BP neural network

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Abstract. Erythrocyte sedimentation rate (ESR) is an important medical test parameter, changes in ESR value can reflect changes in the condition, ESR measurements are susceptible to ambient temperature. This paper proposes a temperature compensation algorithm for ESR measurement based on BP neural network, temperature compensation can be ESR value detection result, to further improve the measurement accuracy erythrocyte sedimentation rate. Firstly, a neural network model of ESR temperature compensation is established. Secondly, learning training samples of the network are obtained and the sample data is pre-processed and network trained. Finally, the network prediction effect is tested to generate an optimal ESR temperature compensation network model. The algorithm proposed in this article can use the neural network method to correct the erythrocyte sedimentation measurement value, and can quickly and accurately achieve temperature compensation of the erythrocyte sedimentation value. This algorithm not only makes the accuracy of the compensation link within the measurement tolerance range, but also for the temperature without training Points have predictive compensation effects.

1. Introduction

Erythrocyte sedimentation rate, referred to as ESR, unit is mm / h, is an important detection index in the field of clinical medicine and medical research¹, and has a reference role for a series of disease diagnosis. Process is also one of the important diagnostic indicators of certain diseases².

In the modern medical field, the traditional manual Wechsler's method, Cooper's method, Wen's method³, etc. and the erythrocyte sedimentation value measured by erythrocyte sedimentation equipment are easily affected by the ambient temperature, from the perspective of medical principles, within a certain range, an increase in temperature can accelerate blood coagulation, otherwise it can delay blood coagulation, because the coagulation process is a series of enzymatic reactions. When the temperature rises, or after the test tube is blown dry with hot air, the remaining heat of the test tube is not dissipated. When another blood sample is taken, the enzyme activity is increased due to the higher temperature and the coagulation reaction speeds up, which will have a certain effect on the measurement of the ESR. In actual clinical detection and medical experiments⁴, it is difficult to ensure...
that the measurement environment reaches the standard temperature of 18 degrees Celsius of the Weiss method. Therefore, the temperature of the erythrocyte sedimentation detection value needs to be corrected.

In the traditional method for detecting the ESR value, the ESR temperature compensation table is often used for formula correction, that is, the detection value is brought into the equation for temperature correction. This method is more complicated to use and the accuracy of the ESR value is not high. In addition, there is another type of method for temperature compensation through a linear fitting algorithm. This method has a limited accuracy improvement over the formula method, in order to further improve the measurement accuracy of the ESR measurement value, the inherent nonlinear mapping capability of the artificial neural network is used to approximate the nonlinear function with high accuracy. Therefore, a better neural network mathematical model can be established to obtain a more accurate compensation value of blood sedimentation temperature, so as to further improve the measurement accuracy of blood sedimentation value.

2. Basic principles

A large amount of erythrocyte sedimentation value test data shows that as the measurement ambient temperature increases, the erythrocyte sedimentation value also gradually increases, and the larger the temperature deviation, the larger the deviation from the standard value. Therefore, the temperature difference between the measured ambient temperature and 18°C can be used as a characteristic quantity to reflect the change of the hemorrhagic sedimentation value under different measured ambient temperatures. BP neural network model consists of input layer, hidden layer and output layer, select the uncorrected erythrocyte sedimentation measurement value and the temperature difference between the measured ambient temperature and 18°C corresponding to the measurement value as the input layer unit of the BP neural network, and select the standard value of the erythrocyte sedimentation unit as the output layer unit. At this point, BP neural network is a double-input-single-output network structure.

By establishing the error expression of the expected value and the output value, according to the gradient descent algorithm, the weight adjustment amount of each node of the model can be obtained, and the optimal BP neural network ESR value compensation model and corresponding parameters are obtained. Utilizing the good non-linear mapping function of the neural network model, a more accurate erythrocyte sedimentation temperature compensation value can be obtained, which further improves the erythrocyte sedimentation detection accuracy.

3. Temperature compensation method of ESR measurement value based on BP neural network

3.1. Establishing BP neural network model for ESR value and temperature compensation

The neural network model established in this paper to establish the ESR temperature gain compensation consists of an input layer, a hidden layer, and an output layer. The number of input layer nodes is 2, the number of hidden layer layers is 1, the number of nodes is 5, and the number of output layer nodes is 1. Set the number of BP neural network training times to 3000, the learning rate to 0.1, and the minimum mean square error to $10^{-6}$, the uncorrected red blood cell sedimentation measurement value $x_1$ is selected, and the temperature difference $x_2$ between the measurement ambient temperature corresponding to the measurement value and the Webster's standard red blood cell sedimentation temperature 18 is used as the input layer parameter. At this time, the BP neural network is a two-input single-output network structure. The excitation functions of the hidden layer and output layer of the network are tansig function and purelin function.

$$f(x) = \frac{1}{1 + e^{-x}}$$

$$Y^{(0)} = [x_1, x_2]^T = [a_1(0), a_2(0)]^T$$

$$Y^{(1)} = [a_1(1), a_2(1), a_3(1), a_4(1), a_5(1)]^T$$

$$x_1 + x_2 = 18$$

$$Y = [a_1(1), a_2(1), a_3(1), a_4(1), a_5(1)]^T$$
In (Equation 1), $f(x)$ is the tansig expression of the hidden layer and output layer excitation functions. Equations 2 to 4 are input layer parameters, that is, uncorrected erythrocyte sedimentation measurement value $x_1$ and temperature difference value $x_2$, and hidden layer parameters, the mathematical expression of the output layer parameters.

$$Y^{(2)} = [a_i(2)]^T \quad \text{(4)}$$

In (Equation 1), $f(x)$ is the tansig expression of the hidden layer and output layer excitation functions. Equations 2 to 4 are input layer parameters, that is, uncorrected erythrocyte sedimentation measurement value $x_1$ and temperature difference value $x_2$, and hidden layer parameters, the mathematical expression of the output layer parameters.

$$net_i^{(l)} = \sum_{k=1}^{2} W_{ik}^{(l)} y_k^{(0)} - a_l, (1 \leq l \leq 5) \quad \text{(5)}$$

$$net^{(l)} = [net_1^{(l)}, net_2^{(l)}, net_3^{(l)}, net_4^{(l)}, net_5^{(l)}]^T \quad \text{(6)}$$

$$\begin{bmatrix}
W_{11}^{(1)} & W_{12}^{(1)} \\
W_{21}^{(1)} & W_{22}^{(1)} \\
W_{31}^{(1)} & W_{32}^{(1)} \\
W_{41}^{(1)} & W_{42}^{(1)} \\
W_{51}^{(1)} & W_{52}^{(1)} \\
\end{bmatrix}$$

$$W^{(1)} = \quad \text{(7)}$$

$$net^{(l)} = W^{(l)} Y^{(0)} \quad \text{(8)}$$

$$Y^{(1)} = [Y_1^{(1)}, Y_2^{(1)}, Y_3^{(1)}, Y_4^{(1)}, Y_5^{(1)}]^T \quad \text{(9)}$$

$$Y^{(1)} = f(net^{(l)}) \quad \text{(10)}$$

In (Equation 5), the number of hidden layer neurons is 5, $W_{ik}^{(l)}$ is the weight value connecting the $k$th node of the input layer and the hidden layer node $l(1 \leq l \leq 5)$, $y_k^{(0)}$ is the input parameter, and $a_l(1 \leq l \leq 5)$ is the hidden layer threshold. This formula can calculate the calculation value of each node in the hidden layer. (Equation 6) and (Equation 7) define the matrix expressions of the hidden layer output and input layer to hidden layer weights, respectively. (Equation 8) is the formula for solving the output of the hidden layer, (Equation 9) defines the final output matrix of the hidden layer. In (Equation 10), the value in $net^{(l)}$ is brought into the activation function $f(x)$ and solved to obtain the final hidden layer calculation result. \cite{7}

$$net_i^{(2)} = \sum_{l=1}^{5} W_{il}^{(2)} y_i^{(1)} - b \quad \text{(11)}$$

$$net^{(2)} = [net_1^{(2)}]^T \quad \text{(12)}$$

$$W^{(2)} = \begin{bmatrix}
W_{11}^{(2)} & W_{12}^{(2)} & W_{13}^{(2)} & W_{14}^{(2)} & W_{15}^{(2)} \\
W_{21}^{(2)} & W_{22}^{(2)} & W_{23}^{(2)} & W_{24}^{(2)} & W_{25}^{(2)} \\
W_{31}^{(2)} & W_{32}^{(2)} & W_{33}^{(2)} & W_{34}^{(2)} & W_{35}^{(2)} \\
W_{41}^{(2)} & W_{42}^{(2)} & W_{43}^{(2)} & W_{44}^{(2)} & W_{45}^{(2)} \\
W_{51}^{(2)} & W_{52}^{(2)} & W_{53}^{(2)} & W_{54}^{(2)} & W_{55}^{(2)} \\
\end{bmatrix}$$

$$net^{(2)} = W^{(2)} Y^{(1)} \quad \text{(13)}$$

$$Y^{(2)} = [Y_1^{(2)}]^T \quad \text{(14)}$$

$$Y^{(2)} = f(net^{(2)}) \quad \text{(15)}$$

In (Equation 11), $W_{il}^{(2)}(1 \leq l \leq 5)$ is the weight value connecting the $l$th node of the hidden layer and the output layer node, $y_i^{(1)}(1 \leq l \leq 5)$ is the hidden layer output parameter defined by (Equation 9), and $b$ is the threshold value of the output layer. This formula can be used to calculate the output node value. (Equation 12) and (Equation 13) define matrix expressions of output layer output and hidden layer to output layer weights, respectively. (Equation 14) is a formula for solving the output layer result, (Equation 15) defines the final output matrix of the output layer. In (Equation 16), the value in $net^{(2)}$ is brought into the activation function $f(x)$ and solved to obtain the final output layer calculation result, that is, the predicted value of the ESR temperature compensation. In order to minimize the error between the output target and the expected value, an error expression (Equation 17) between the expected value and the output value is established, as follows:

$$Y^{(1)} = f(x) \quad \text{(16)}$$
\[ E = \frac{1}{2} (d - Y^{(2)})^2 \]  

(17)

In (Equation 17), \( E \) is the error signal; In (equation 4), \( d \) is the expected value, that is, the value of the blood sedimentation data of this group at the standard temperature of 18 \(^\circ\)C. According to the gradient descent algorithm, the gradient of \( W^{(1)} \) and \( W^{(2)} \) to \( E \) is calculated respectively, and the weight adjustment formulas of each node in the hidden layer and output layer of the network can be obtained as (Equation 18) and (Equation 19), where \( \eta \) is the learning rate set by the network \[^8\]:

\[ W_{lk}^{(1)} = W_{lk}^{(1)} + \eta Y_i^{(1)} (1 - Y_i^{(1)}) x_l W_l^{(2)} E \quad l = 1,2,3,4,5 \quad k = 1,2 \]  

(18)

\[ W_l^{(2)} = W_l^{(2)} + \eta Y_i^{(1)} E \quad l = 1,2,3,4,5 \]  

(19)

The threshold adjustment formulas for hidden layer and output layer are (Equation 20) and (Equation 21) respectively:

\[ a_i' = a_i + \eta Y_i^{(1)} (1 - Y_i^{(1)}) W_l^{(2)} E \quad l = 1,2,3,4,5 \]  

(20)

\[ b' = b + E \]  

(21)

After continuous adjustment and calculation of weights and thresholds, if the error value is less than the set minimum mean square error, the network training is completed, and the corresponding weights and threshold data are saved, and the temperature compensation nonlinear formula can be fitted at the same time. (Equation 1) to (Equation 21) constitute a mathematical model of high-precision erythrocyte sedimentation temperature compensation.

3.2. Sample data acquisition and pretreatment

In order to use BP neural network to realize temperature compensation of serum sedimentation rate, training samples of temperature compensation model should be obtained. Needs to sample data collecting blood sedimentation temperature range is 16 \(^\circ\)C to 33 \(^\circ\)C, unit interval 1 \(^\circ\)C, and record the corresponding environmental temperature, at the same time set up the environment temperature of 18 \(^\circ\)C, sample data obtained the corresponding standard value of blood sedimentation, stay fixed blood sedimentation value and standard value of blood sedimentation by blood sedimentation detection device, through the temperature sensor for measuring temperature environment.

Since the blood sedimentation values of the collected samples vary greatly, and the effective range of tansig is between 0 and 1, the collected training data should be normalized. The following formula is adopted for normalization:

\[ X = 2 * \frac{x - x_{\min}}{x_{\max} - x_{\min}} - 1 \]  

(22)

In (Equation 22), \( x \) is the original data and \( X \) is the normalized data. \( x_{\min} \) and \( x_{\max} \) correspond to the minimum and maximum values of the original data, respectively.

3.3. Network training was conducted on the number of samples

Assign each connection weight a random number within the interval (-1, 1), set the error function \( e \), and give the calculation precision value and the maximum learning times \( M \). The KTH input sample and the corresponding expected output were randomly selected to calculate the input and output of each neuron in the hidden layer. Using the expected and actual output of the network, the partial derivative of the error function to each neuron in the output layer is calculated, and the global error \( E \) is calculated to determine whether the network error meets the requirements. When the error reaches the preset accuracy or the learning number is greater than the set maximum, the algorithm is terminated. Otherwise, select the next learning sample and the corresponding expected output, return to the previous step and enter the next round of learning \[^9\].
3.4. Test the network prediction effect

Enter the prepared validation data to check if it is within the desired accuracy. If the predicted value and expected value error are less than or equal to the preset target error, the weight and threshold data of each layer of the neural network are saved to generate the optimal network model. After the measured blood sedimentation rate is obtained, the corrected blood sedimentation rate can be obtained through the output of the optimal network model. The overall flow chart of the BP neural network blood sedimentation rate temperature compensation method proposed in this paper is shown in figure 1, and the flow chart of the BP neural network temperature compensation algorithm is shown in figure 2.

4. Experimental analysis

This paper established the BP neural network the blood sedimentation value temperature compensation model, under the standard temperature 18 °C by westergren method to obtain samples for standard blood sedimentation value, through the blood sedimentation detection device for more groups sample data for training, trained to get the optimal model parameters, generate optimal temperature compensation model, and selects the 15 set of validation data for validation. At the same time, the traditional blood-sedimentation rate temperature compensation method was used to compare the compensation results. The results are as follows:
Figure 3 and figure 4 respectively show the compensation curves and error curves corresponding to one set of verification data. Table 1 shows the temperature compensation results of eight sets of verification data. The experimental and data results show that the compensation accuracy of the model is within the preset error range. Compared with the traditional temperature compensation method, the compensation accuracy of the blood sedimentation value can be further improved to achieve a high precision temperature compensation for the measured value of blood sedimentation.

5. Conclusion
This paper proposed a new temperature compensation method can blood sedimentation value using the BP neural network model to simulate the blood sedimentation measuring value correction, can achieve rapid and accurate blood sedimentation value of temperature compensation, not only make the precision of the compensation link allowed error range, not practice and for the temperature of the point has predictive compensation effect, compared with the traditional blood sedimentation value of the temperature compensation method, this method can improve the measuring accuracy of blood sedimentation value.

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