Soybean Appearance Quality Discrimination Model Based on BP Neural Network Optimized by Convergence-Improved LP Algorithm

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Abstract
In view of the bad performance of standard BP neural network algorithm in soybean appearance quality discrimination, this paper put forward a BP neural network optimized by improved LP algorithm. It firstly combines the principal component analysis with BP neural network, using the principal component analysis method to preprocess the high-dimensional input variables to construct the low-dimensional principal variables which reflects the process information, then using the global properties of Gradientdescent and local properties of Gaussian- Newton algorithm built in LM algorithm to train the BP neural network. The simulation experiment shows that the BP neural network optimized by LM algorithm in this paper has better convergent performance and image identification ability compared with standard BP neural network. The proposed BP algorithm shows good performance in soybean appearance quality identification.
Key words: NEURAL NETWORK, SOYBEAN APPEARANCE, QUALITY DISCRIMINATION, LM ALGORITHM, CONVERGENCE OPTIMIZATION

Introduction

As an important economic crop in the world, soybean has been enjoyed by people of all ages for its economic value and edible value. Soybean industry has been fully integrated into the people's daily lives in China where soybean is mainly produced [1]. The quality improvement of soybean, the production and testing of special varieties have important significance for ensuring the benefit of soybean farmers and processing enterprises, and finally improving the whole benefit of soybean industry chain. Image processing technology can reflect the external quality and characteristics like sample size, shape and defect, realize the objective, accurate, rapid and real-time online detection of agricultural products, and carry out the quantitative analysis and qualitative evaluation [2]. Spectral technology can reflect the physical structure, chemical composition and other intrinsic quality of agricultural products. Therefore, the comprehensive quality of agricultural products can be detected by using hyper-spectral imaging technology [3].

With the development of image technology and chemometrics, the optical detection methods have been widely developed and applied in the quality and safety inspection of agricultural products. Among them, machine vision and near infrared spectroscopy analysis technique are typical ones. Fang et al presented three methods for the detection of rice grains, namely histogram Fourier coefficient discriminant method, histogram peak detection method and gray mutation method, in order to detect the cracking mechanism of rice [4]. Xu Li et al combined the theory of machine vision with color theory to study the division method of the different color features of the rice endosperm, the cortex and embryos after staining. Luo et al studied the detection techniques of standard wheat and six kinds of damaged wheat kernels based on four morphological parameters and twenty four kinds of color parameters, using nonparametric discriminant analysis method. The experimental results show that the recognition accuracy of the proposed method is 92.5% for standard wheat, and the recognition accuracy for six kinds of broken wheat is 90.3%, 98.6%, 99%, 99.1%, 97.5% and 100% respectively. M. Nair studied the detection technology of surface stain of wheat based on morphological parameters and color parameters [6]. When morphological parameters were used alone, the recognition accuracy rate was 89.4%; when color parameters were used alone, the accurate rate of recognition was 71.4%; when these morphological parameters and color parameters were combined, the accurate rate was 93.2%. Paliwal researched technique for the identification of different wheat varieties based on color parameters and Fourier descriptors with the minimum distance classifier, and the identification accuracies of five kinds of Canadian wheat were 100%, 94%, 93%, 99% and 95% [7]. Steenhoek et al studied the detection technique of corn moldy grain and damaged grains. They took directly RGB pixel values of the original image as feature parameters, and the accuracy rate reached 92% by using the probabilistic neural network classifier [8]. Cardarelli proposed to take the average value of R, G and B component as discriminant parameter in the detection of the damaged grains and the recognition accuracy rate on three kinds of damaged grains reached to more than 80% [9]. In the distinction of bulk wheat varieties, Manickavasagan et al found that the gray values of different kinds of wheat were significantly different. Under the same moisture content, quadratic linear analysis precision could reach more than 92% [10]. Based on machine vision, Tahir discussed the relationship of different water content with color, structure, morphological characteristics among three kinds of wheat, showing that bulk grain had obvious relation between water content and color and structure properties compare with single hulled grain [11].

The detection techniques of intact wheat and damaged wheat were studied respectively in Luo group by using K-nearest neighbor method based on statistical classifier and the classifier based on BP network. The test results showed that the accuracy of recognition based on BP network classifier was higher than that of recognition based on statistical classifier [12]. Shatadal conducted the research on the detection technology of hard, non-hard and partially hard wheat and used BP network classifier to reach a very good detection effect [13]. Liao. K et al. studied the detection technique of intact corn kernels and damaged grains. They selected the morphological parameters as the feature parameters and adopted the BP network classifier, and found the average accuracy rate was 95% [14]. Song Tao used the machine vision for grain shape recognition research, with artificial neural network to identify the complete and broken corn particles, and studied the fractal description and recognition on the grain surface lesions [15].

In view of the defects of BP neural network algorithm, this paper has proposed an optimized BP neural network model by improved LM algorithm in soybean exterior quality evaluation, and simulation results have been conducted to verify the effectiveness of this improved strategy.

Morphology identification model based on BP neural network

People get the artificial neural network algorithm through simulating the structure and function of cerebrum. Artificial neural network algorithm has the advantages of intelligence, convergence and robustness. There are hundreds of neural network models, and the typical one in reality is BP neural network. It is a multilayer feed-forward network with S-type neuron transfer function. Output is continuous quantity from 0 to 1, which realizes the arbitrary non-linear mapping from input to output. The basic structure model of BP neural network is shown below.

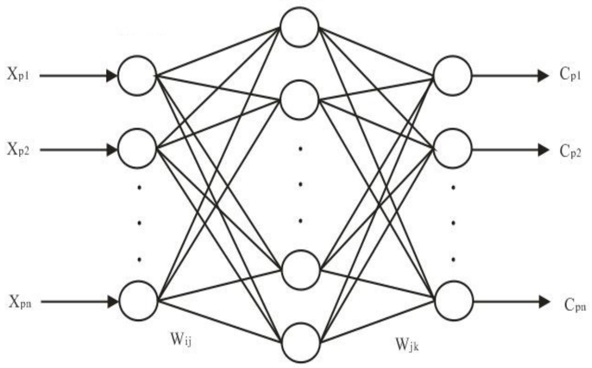

Figure 1. Neural network model diagram

The BP neural network algorithm has the following descriptions.

$$S_{pj} = \sum_{i=1}^{n} w_{ij} \cdot x_{pj} - \theta_j \quad (1)$$

$$b_{pj} = f(S_{pj}) \quad (2)$$

$$t_{pk} = \sum_{i=1}^{L} w_{jk} \cdot b_{pj} - \gamma_k \quad (3)$$

$$C_{pk} = g(t_{pk}) \quad (4)$$

Feedforward calculation and error reverse adjustment is the learning process of neural network. Taking logarithm Sigmoid function as the excitation function, the error back propagation progresses as follow.

To value the connection weight and threshold with random number;

To calculate from equation (1) to equation (4);

To calculate the K neuron error δ_{pk} of output layer corresponding to sample P in following equation;

$$\delta_{pk} = C_{pk}(1 - C_{pk})(y_{pk} - C_{pk}) \quad (5)$$

To obtain the j neuron error δ_{pj} of output layer corresponding to sample P in following equation;

$$\delta_{pj} = b_{pj}(1 - b_{pj}) \sum_{j=1}^{L} w_{jk} \delta_{pk} \quad (6)$$

To calculate the connection weight between output layer and middle layer and threshold adjustment of output layer;

$$\Delta w_{jk} = \beta b_{pj} \delta_{pk} \quad (7)$$

$$\Delta \gamma_k = \beta \delta_{pk} \quad (8)$$

To calculate the connection weight between input layer and middle layer and threshold adjustment of middle layer;

$$\Delta w_{ij} = \beta b_{pt} \delta_{pj} \quad (9)$$

$$\Delta \theta_j = \alpha \delta_{pj} \quad (10)$$

To obtain the new connection weight and threshold;

To put the new weight and threshold into (2) to restart the operation;

To judge whether it meet the requirement $y_{pk} - C_{pk} | < \varepsilon$ (ε is an accurate value), if it is, the algorithm ends.

The identification model based on BP neural network is shown in Figure 2.

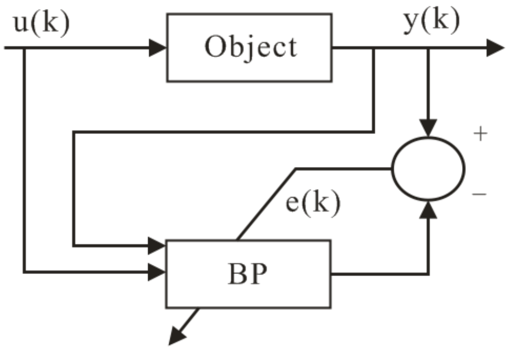

Figure 2. Identification model based on BP neural network

$u(k)$ and $e(k)$ are the input value of the two input terminals in the identifier; $y(k)$ is the expected output and $y_0(k)$ is the output through BP neural network. The value of $e(k) = y(k) - y_0(k)$, namely the error, is selected as the teacher signal of BP neural network learning.

BP neural network model based on convergence-improved LM algorithm

Data preprocessing based on PCA

The main variables that reflect the information of the data are obtained by principal component analysis (PCA), and the effects of the secondary variables are ignored, which improves the operation speed in the statistical modeling. Obviously, for this kind of black box model, if the input variables of neural network can be preprocessed to eliminate irrelevant variables and extract the relationship between input variables with a small amount of irrelevant comprehensive variables, it will reflect most of the information contained in the original high-dimensional variables, which will not only simplify the structure and size of the network model, but also improve the efficiency and accuracy of the model.

This paper combines the PCA method with artificial neural network BP algorithm: firstly PCA is used to preprocess the high-dimensional input variables to construct low dimensional principal component variables which reflects the process information; then, the neural network BP algorithm is used to establish a self-tuning model for principal component variables. This method not only simplifies the structure of the neural network model but also can make use of the PCA method to extract artificial and instrumental error so as to avoid error output of model. In this paper, the soft sensor model can be quickly established with high accuracy by using this method.

Because of the small amount of data, the input data is two dimensional, and the structure of the PCA-BP model is as follows:

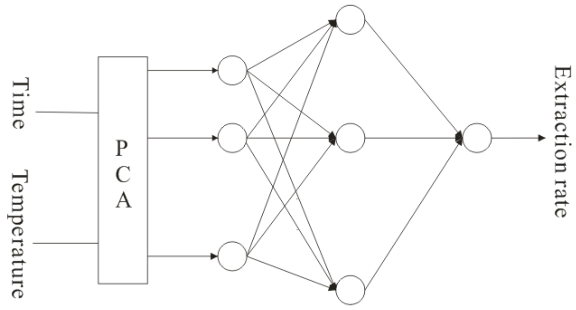

Figure 3. PCA-BP model

BP neural network consist of three layers. Input layer has five neurons corresponding to five principal components. Hidden layer also has five neurons. Output layer only has one neuron corresponding the extraction rate. The learning rate of the neural network is 0.9, momentum factor 0.6 and iteration number 500 in the training.

Neural network model based on convergence-optimized LM algorithm

LM algorithm has both the local convergence ability of Gauss-Newton algorithm and the global property of Gradient descent algorithm.

$$\omega = [\omega_1, \omega_2, ..., \omega_x]^T \quad (11)$$

$\omega(k)$ represents the network weight of k iteration, and the new weight vector $\omega(k+1)$ can be obtained through equation (12),

$$\omega(k+1) = \omega(k) + \Delta\omega \quad (12)$$

In-out sample couples are expressed as $\{(x^l, t^l), ..., (x^\xi, t^\xi), ..., (x^m, t^m)\}$ where o^ξ is input and x^ξ is output.

$$E(\omega) = \frac{1}{2}\sum_\xi (e^\xi)^2 = \frac{1}{2}\sum_\xi (t^\xi - o^\xi)^2 \quad (13)$$

For Newton algorithm, there is,

$$\Delta\omega = -[\nabla^2 E(\omega)]^{-1} \nabla E(\omega) \quad (14)$$

Here, $\nabla^2 E(\omega)$ is the Hessian matrix of error cost function; $\nabla E(\omega)$ is gradient.

$$\nabla E(\omega) = J^T(\omega) e(\omega) \quad (15)$$

$$\nabla^2 E(\omega) = J^T(\omega) e(\omega) + S(\omega) \quad (16)$$

Among them,

$$e(\omega) = (e^1, e^2, ..., e^m)^T \quad (17)$$

$$S(\omega) = \sum_\xi e^\xi(\omega) \nabla^2 e^\xi(\omega) \quad (18)$$

$J(\omega)$ is the Jacobian matrix, namely,

$$J(\omega) = \begin{bmatrix} \frac{\partial e_1(\omega)}{\partial \omega_1} & \frac{\partial e_1(\omega)}{\partial \omega_2} & \cdots & \frac{\partial e_1(\omega)}{\partial \omega_n} \\ \frac{\partial e_2(\omega)}{\partial \omega_1} & \frac{\partial e_2(\omega)}{\partial \omega_2} & \cdots & \frac{\partial e_2(\omega)}{\partial \omega_n} \\ \cdots & \cdots & \cdots & \cdots \\ \frac{\partial e_N(\omega)}{\partial \omega_1} & \frac{\partial e_N(\omega)}{\partial \omega_2} & \cdots & \frac{\partial e_N(\omega)}{\partial \omega_n} \end{bmatrix} \quad (19)$$

For Gauss-Newton algorithm,

$$\Delta\omega = -[J^T(\omega) J(\omega)]^{-1} J^T(\omega) e(\omega) \quad (20)$$

LM algorithm is the improvement of Gauss-Newton algorithm, therefore,

$$\Delta\omega = -[J^T(\omega) J(\omega) + \mu I]^{-1} J^T(\omega) e(\omega) \quad (21)$$

where μ is the damping coefficient; I is the unit matrix. From equation (21), it is known when $\mu = 0$, the equation becomes the Gaussian-Newton algorithm; when μ large, LM algorithm is close to Gradientdescent algorithm, and μ will decrease after each iteration meaning the value becomes closer to the objective error value. At this time, LM algorithm will approximate to Gaussian-Newton algorithm with high operation speed and accuracy.

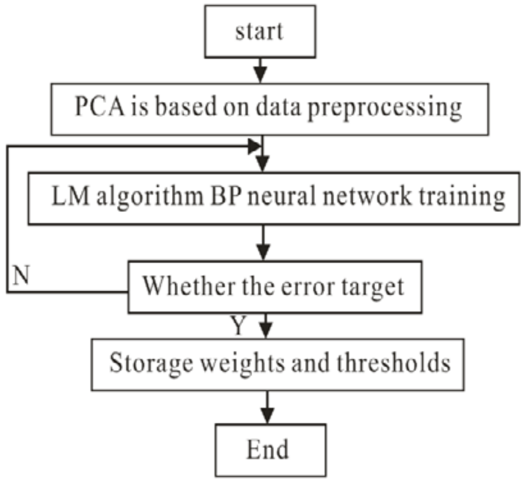

Figure 4. BP network training steps of LM algorithm

BP neural network is trained by the global property from Gradientdescent and local feature from Gaussian-Newton algorithm built in LM algorithm. The training process is shown in figure 4.

Simulation experiments

In order to verify the efficiency of the improved BP neural network algorithm, this paper conducted the simulation experiments. All the simulation was operated in the computer with following equipment: CPU-Intel Core i7; Memory 8GB; Windows8 operation system; Simulation software-Matlab2011b(X64).

Test object function

$$y(k+1)=e^{u(k)}\sin(2\pi\cdot u(k)) \quad (22)$$

Training function

$$u(k)=4\cdot(rand-0.5) \quad (23)$$

Test signal

$$u(k)=2\sin(\pi t/100) \quad (24)$$

The structure of BP network is 2-4-1distributed by neurons in each layer: two neurons in input layer; four neurons in hidden layer; one neuron in output layer. The leaning rate of BP algorithm is $\eta=0.5$; In LM algorithm, $\mu=0.01$, $\beta=10$ and the training number is 200. Standard BP neural network algorithm and improved BP neural network algorithm by LM algorithm have been tested. The comparison results are shown below.

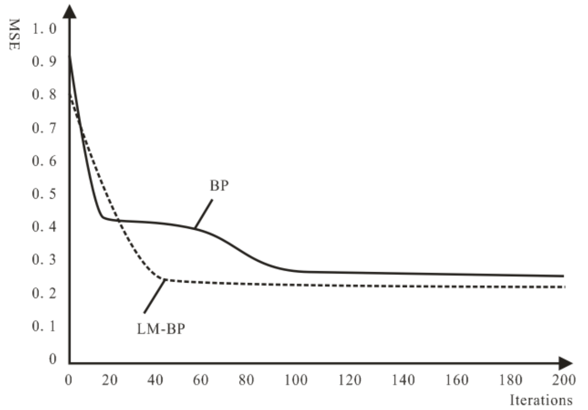

Figure 5. MSE comparison results of test function 1

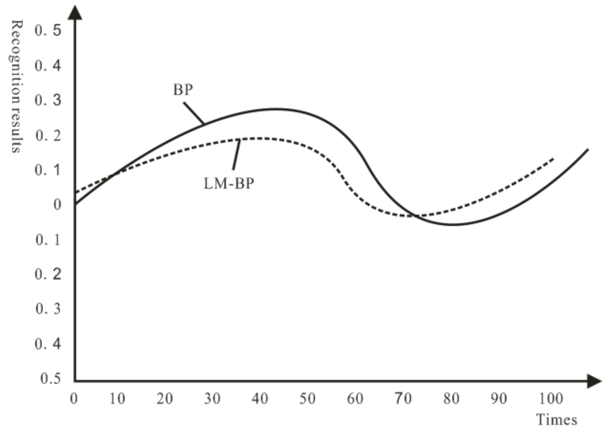

Figure 6. Comparative identification results of test functions 1

(2)Test object function:

$$y(k)=u^3(k)+\frac{y(k-1)}{1+y^2(k-1)} \quad (25)$$

Training function:

$$u(k)=2\cdot(rand-0.5) \quad (26)$$

Test signal:

$$u(k)=0.5\sin(6\pi t/100) \quad (27)$$

The structure of BP network is 2-6-1, distributed by neurons in each layer: two neurons in input layer; six neurons in hidden layer; one neuron in output layer. The leaning rate of BP algorithm is $\eta=0.5$; In LM algorithm, $\mu=0.01$, $\beta=10$ and the training number is 200. Standard BP neural network algorithm and improved BP neural network algorithm by LM algorithm have been tested. The comparison results are shown below.

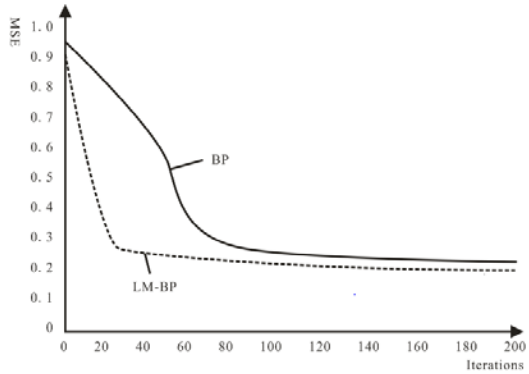

Figure 7. MSE comparison results of test function 2

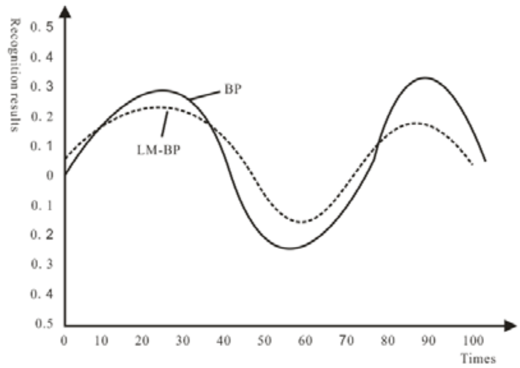

Figure 8. Comparative identification results of test functions 1

Then we compare these two algorithms in the quality identification of soybean. The results are as follows.

Figure 9. Soybean appearance quality discrimination results by standard BP algorithm

Figure 10. Soybean appearance quality judgment results by improved BP algorithm

It is apparent from the comparison above that the BP neural network optimized by LM algorithm in this paper has better convergent performance and image identification ability compared with standard BP neural network. The proposed BP algorithm shows good performance in soybean appearance quality identification.

Conclusions

Soybean is an important cash crop in China, but the inspection of soybean appearance as an important link in the soybean production and processing, the detection means still remain in the low-end traditional artificial way. The detection results were not intuitively quantified and systematized. There is no accurate detection results for soybean product classification, which seriously restricts the development of soybean industry in our country. Therefore, in view of the defects in current BP neural network algorithm, this paper put forward an optimized BP neural network based on LM algorithm for the soybean appearance quality identification. The simulation experiment shows that the BP neural network optimized by LM algorithm in this paper has better convergent performance and image identification ability compared with standard BP neural network. The proposed BP algorithm shows good performance in soybean appearance quality identification.

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