Research on Classification Method of Vehicle Body Surface Defects Based on BP Neural Network

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Abstract: In order to classify the surface defects of the vehicle body, a classification method based on BP (back propagation) neural network is proposed. According to the characteristics of vehicle body defects, the gray, morphological and geometric features of various defects were extracted, and the defect feature database was established. The defect classifier was designed by using improved BP neural network algorithm. The experimental results show that the method is very feasible and effective in the identification of vehicle body defects.

1. Introduction
In the processing of the body stamping parts, since the process after the appearance inspection will eliminate the influence of some minor defects on the body quality, the standard of the vehicle body surface inspection is determined according to the type of defects, such as line marks. Whether the length exceeds the standard, whether the oil stain and the scratched area exceed the standard, and if there is crack or wrinkle, it is judged as waste, so the defect needs to be classified[1].

When the image of each defect image is obtained by the image segmentation algorithm, the defect target needs to be classified. The neural network essentially implements a nonlinear mapping process from input to output, with memory and learning functions, and can obtain very accurate recognition results in complex system identification[2]. Based on this, this paper uses the improved BP neural network algorithm to study the classification method of vehicle body surface defects.

2. Feature Description
The purpose of image feature extraction and selection is to ensure the accuracy and rapidity of classification. The purpose of image feature extraction and selection is to ensure the accuracy and rapidity of classification. It is necessary to select the feature that the distance between the types in the feature vector space is large and the internal variance of the type is small, that is, the different types of feature values are far away, and the feature values inside the same type are densely aggregated. The surface defects of the vehicle body have the characteristics of gray level difference, shape difference, geometric difference, etc. In this paper, the gray level feature, shape feature and minimum enclosing rectangle (MER) are selected: When the boundary of a target object is known, the easiest way is to characterize its basic shape with a minimal circumscribed rectangle. In this paper, taking the aspect ratio of the minimum circumscribed rectangle as the eigenvalue is particularly effective for distinguishing the slender type of defects. The direction is the direction of the longest side of the smallest circumscribed rectangle, and the range of the defect direction similar to the line mark type is small, and the oil stain can be in any direction. Rectangularity: It is characterized by the ratio of the area of the object to the area of the smallest circumscribed rectangle, reflecting the fullness of the
object's external rectangle. The squareness value of the pit is significantly different from other types of defects. The centroid coordinates reflect the position information of the defect, and the abscissa has a good effect on distinguishing the mouth defects, while the ordinate has little effect on distinguishing the defect types and does not need to be used. The average gray value and the mean square error reflect the grayscale characteristics of the defect, which can reflect the bright and dark characteristics of the defect.

3. BP neural network classifier design
The classifier design is to train the training samples to the neural network to determine the weight matrix and offset vector of each layer, and use the obtained network structure to identify the defects to be identified.[3]

3.1 Input layer and output layer design
The input and output layers of the BP neural network are designed according to the requirements of the user. In order to avoid the influence of the large value feature on the classification more than the small value feature, all the feature values should be as large as an order of magnitude. The feature is processed, and 7 feature values are selected as the classification index of the vehicle body surface defect, including the aspect ratio, the direction offset amount, the abscissa occupation ratio, the squareness, the logarithm of the density, and the average gray value. The gradation ratio and the gamma mean square error, and the eigenvectors are used as the input of the neural network, then the number of input neurons is 7.

The 6 defects to be identified: oil stains, scratches, line marks, cracks, pits and wrinkles are used as the output of the neural network, and the number of output neurons is six. In the training set sample, if a class belongs to the kth class, the target output is set to $y=(0,...,0,1,0,...,0)$, the kth column is set to 1.

3.2 Hidden layer design
The hidden layer determines the nonlinear mapping ability of the BP neural network. The number of layers and nodes (neurons) of the hidden layer need to be determined. In general, increasing the number of hidden layers can reduce network errors and improve performance, but it also makes the network is complicated and tends to have an "over-fitting" tendency. The BP neural network has at least one hidden layer, and the two hidden layer neural networks can satisfy any classification requirement[4-5]. Considering the network input layer and output layer the number of neurons is not a lot. Here, a single hidden layer is used, and the structure is shown in Figure 1.

![Three-layer neural network structure](image)

Figure 1 Three-layer neural network structure

If the number of hidden layer units is too small, the network may not be trained, or the accurate features of the samples cannot be extracted. The samples that have not been seen before are not recognized, and the fault tolerance is poor. However, too many hidden layer units may cause the network structure to be too complicated and increase. The training time will also make the feature
space too thin and lose the generalization ability. For general practical applications, the following empirical formula can be referred to:

\[ N = \sqrt{n + m + a} \]  

Here: \( m \) is the number of neurons in the output layer; \( n \) is the number of neurons in the input layer; \( a \) is a constant between \([1, 10]\), and the classification effect is better when the number of experimental nodes is 9.

3.3 Activation function selection

In order to derive the iterative training algorithm, calculate the synaptic weight of the neural network, and minimize the chosen cost function, the activation function must be able to differentiate. Here, the most commonly used sigmoid function in the continuous differential function is selected as the activation function. The function is as follows:

\[ f(x) = \frac{1}{1 + e^{-ax}} \]  

3.4 Network learning algorithm

The BP algorithm compares the output of the network with the desired value, and calculates some error measure based on the variance and then uses the gradient descent method to adjust the network weight to minimize the error. The standard neural network algorithm convergence process is very slow, by introducing the momentum term an improved neural network algorithm[6] that allows the convergence process to pass faster through the smooth portion of the loss surface. \( v \) is the training mode that represents body defects, \( y \) is the actual output corresponding to the defect, \( w \) is the desired output, the learning algorithm is as follows:

- Weighting with a small random number \( w_{ij} \) Assign and let \( k = 0 \).
- Enter a vector \( v \) in the defect training set to calculate the output \( y \) of the neural network.
- If the output defect type vector \( y \) does not match the expected output vector \( w \), the weight is adjusted as follows

\[ w_{ij}(k + 1) = w_{ij}(k) + \varepsilon \delta_j z_i(k) + a[w_{ij}(k) - w_{ij}(k - 1)] \]  

Here: \( \varepsilon \) is the rate of learning; \( z_i(k) \) is the output of node \( i \); \( k \) is the number of iterations; \( \delta_j \) is the error associated with node \( j \) in the adjacent upper layer: \( \delta_j = y_j(1 - y_j)(w_j - y_j) \) is the output node \( j \):

\[ \delta_j = z_j(1 - z_j)(\sum_{t} \delta_t w_{jt}) \]  

- Go to step 2 and read the next defect training pattern vector.
- Increment \( k \), repeat steps 2 through 4 until the network outputs the desired result for each defect training mode.

4. Experimental results

Classifiers often use their false positive rate as a test for classifier performance. A total of 160 training samples of oil stains, abrasions, line marks, cracks, pits, and wrinkles were used for network training, and 52 unknown defect samples were tested with the obtained classifier. The number of input layer neural units in the experiment was tested. There are 7 output layers, 1 hidden layer, and 9 nodes. The results are shown in Table 1. It can be seen that the classification accuracy of the classifier of the neural network algorithm is relatively high overall. In the experiment, the number of nodes with double hidden layers or smaller is also tried to train the samples, but the classifier approximates the features of the line marks and cracks. The rate of false positives will increase when defects occur.
### Table 1. Classification results

| Category      | Oil stain | Bruise | Line mark | Crack | Pit | Fold | False positive rate % |
|---------------|-----------|--------|-----------|-------|-----|------|-----------------------|
| Oil stain     | 5         | 1      | 0         | 2     | 0   | 0    | 16.7                  |
| Bruise        | 1         | 9      | 0         | 0     | 0   | 0    | 10                    |
| Line mark     | 0         | 0      | 12        | 2     | 0   | 0    | 14.3                  |
| Crack         | 0         | 0      | 1         | 8     | 0   | 0    | 11.1                  |
| Pit           | 0         | 0      | 0         | 0     | 7   | 0    | 0                     |
| Fold          | 1         | 0      | 0         | 0     | 0   | 5    | 16.7                  |

### 5. Conclusion

According to the characteristics of the surface defects of the vehicle body, 160 training samples are trained. The experimental results show that the method is very feasible in the identification of vehicle body defects. Since the number of training samples will limit the classification performance of the BP neural network algorithm, improve the performance of the classifier and identify the types of defects by increasing the number of defective samples.

### Acknowledgement

This article is grateful to the Anhui Provincial Department of Education Natural Science Fund's key project "Study on the Law of Surface Damage Caused by Deep Drawing of Automotive Galvanized Sheets" (No. kj2018a0604), and thanks to the experimental materials provided by Hefei Yili Machinery Manufacturing Co., Ltd.

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