A steel classification algorithm based on surface defects

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Abstract: In the research of image recognition and classification, image retrieval, image data mining, and so on, feature extraction is the basic work, among which the texture feature of an image is of great significance to describe the content of the image. In this paper, an extraction method of steel texture features based on a gray co-occurrence matrix is presented, and the influence of various structural parameters on the structure is analyzed. The feature extraction of specific texture images based on a gray level co-occurrence matrix is realized, and the data classification is carried out by using a probabilistic neural network.

1. Introduction

Steel materials, as a commonly used basic construction material, play a decisive role in the strength and stability of the entire building. The level of carbon content determines the hardness of steel\textsuperscript{[1]}. As the content increases, the plastic shape of the steel will decrease, which is extremely disadvantageous in engineering seismic design. Construction engineering requires steel to meet the requirements of the overall plasticity of the structure under the premise of meeting material strength.

In the production of steel, due to the different raw materials and the influence of the production process, some quality problems may occur in steel products, such as surface dimensional tolerances and surface defects. These quality problems are difficult to eliminate due to the instability of the production process. The quality problems of general steel products can be roughly divided into internal defects and external defects. The internal defects require some instruments for damage or non-destructive testing to get the results. Most of the surface defects can be confirmed by computer vision. These common quality defects are scratches, stutters, pits, bubbles, delamination, and so on. The reasons for these quality problems may be many.

With the advancement of science and technology and the increase of labor costs, the use of professional equipment to directly judge and analyze is also the development direction of future defect detection. The progress of society at any time will continue to produce new detection technologies, which can better adapt to this fast-paced social development. But at present, the machine also has certain limitations. In some cases, these data standards cannot fully reflect the seriousness of the defect. Degree and the use of artificial methods can solve this problem through subjective judgment.

2. Feature Extraction Algorithm

2.1. Basic principles

Image texture features\textsuperscript{[2]}, as a very common feature, are difficult to characterize in images. Texture features generally exist on the surface of rigid objects in nature. Using texture features is a common
method to describe and identify objects.

The texture feature represents the local rules that frequently appear in the image and the arrangement rules of pixels, that is, some rules of the change of the image's gray value. The image can be regarded as a combination of different texture regions.

2.2. Texture feature extraction

The image texture feature extraction method given in this article is based on statistics. The method is based on the gray value of a certain pixel and its neighborhood to calculate the image characteristics in a specific area. And because the statistical data obtained by the gray-level co-occurrence matrix [3] (GLCM) has a good degree of recognition, this method is chosen to extract texture features.

2.3. Gray-level co-occurrence matrix

The joint probability density between two pixels in the image [4] is used to define the co-occurrence matrix. The dispersion characteristic of the image's brightness is represented by this matrix, which is the second-order statistical feature of the image's brightness change. Because the gray value of the image frequently appears in the spatial distribution, there must be a correlation gray-level relationship between pixels at a certain distance. The texture is described by studying the spatial correlation characteristics of the gray level, that is, the gray level co-occurrence matrix.

2.4. Feature extraction based on GLCM

This paper selects five statistics based on the gray level co-occurrence matrix, which are the second-order moment, contrast, correlation measure, entropy, and inverse gap [5][6][7][8][9]. The image texture is rough, and the value of the second-order moment is large, which represents the texture features of the image with regular changes; the image texture is fine, and the value of the second-order moment is small, which represents the relatively scattered and irregular texture features in the image.

The calculation formula is:

\[ E = \sum_{i=0}^{L-1} \sum_{j=0}^{L-1} P^2(i, j) \]  \hspace{1cm} (1)

Contrast represents the clarity of the image and the depth of texture features. The deeper the texture feature, the greater the contrast and the clearer the effect; on the contrary, the lower the contrast and the blurrier the effect.

The calculation formula is:

\[ C = \sum_{i=0}^{L-1} \left\{ \sum_{j=0}^{L-1} \sum_{t=0}^{L-1} P^2(i, j) \right\} \]  \hspace{1cm} (2)

P is the gray-level co-occurrence matrix, L is the dimension of the gray-level co-occurrence matrix, and t is the distance between two pixels.

The correlation measure represents the correlation of local gray values in the image. When the element values of the gray-level co-occurrence matrix are uniformly equal, the correlation measure is large; on the contrary, the correlation measure is small.

The calculation formula is:

\[ R = \frac{1}{\sigma_1 \sigma_2} \left\{ \sum_{i=0}^{L-1} \sum_{j=0}^{L-1} ijP(i, j) - \mu_1 \mu_2 \right\} \]  \hspace{1cm} (3)

among them:

\[ \mu_1 = \sum_{i=0}^{L-1} \sum_{j=0}^{L-1} P(i, j) \]  \hspace{1cm} (4)

\[ \mu_2 = \sum_{j=0}^{L-1} \sum_{i=0}^{L-1} P(i, j) \]  \hspace{1cm} (5)
The entropy of an image represents the degree of inhomogeneity or complexity of texture features and plays an important quantitative index in the image. When the values of all elements in the gray-level co-occurrence matrix are almost equal, when the elements in the co-occurrence matrix are scattered, the entropy value of the image is larger. If the gray level co-occurrence matrix is almost zero, the entropy value of the image is small, and it means that there is no texture feature information in the image.

The calculation formula is:

$$E_n = - \sum_{i=0}^{L-1} \sum_{j=0}^{L-1} P(i, j) \log P(i, j)$$   \hspace{1cm} (8)

The inverse gap represents the homogeneity of the image texture and is a measure of the local change in the image texture. A large value indicates that the image texture lacks variation among different areas, and the local area is very uniform.

The calculation formula is:

$$D = \sum_{i=0}^{L-1} \sum_{j=0}^{L-1} P(i, j) \frac{1}{1+(i-j)^2}$$   \hspace{1cm} (9)

2.5. Analysis of simulation results

Figure 1 Original data and tailored data

![Figure 1 Original data and tailored data](image)

Figure 2 Gray-level co-occurrence matrix extraction parameters of steel pictures

The original image pixels are too large, so the target area is cropped out by cropping, and then the color image is converted to grayscale through image preprocessing, and then the cropped initial ROI area is OSTU segmented \[^{10}\], and then segmented. After the image is corroded and expanded \[^{11}\] to obtain the mask image, the mask image and the initial ROI area image are multiplied to obtain the final ROI area, and the histogram equalization \[^{12}\] is performed on this ROI, and the gray level symbiosis is used. The matrix calculates each parameter.

3. Classification of Steel Pictures

3.1. Basic principles

The probabilistic neural network was first proposed in 1989. It is a branch of radial basis networks and
belongs to a kind of feedforward network. The simple learning process, fast training speed, accurate classification accuracy, and good fault tolerance are all its advantages.

The probabilistic neural network has four layers: the input layer, hidden layer, competition layer, and output layer. Among them, the input layer is responsible for passing feature vectors into the network, and the number of input layers is the number of sample features. The hidden layer is connected with the input layer through the connection weights, the matching degree of the input feature vector and each pattern in the training set is calculated, and the distance is sent to the Gaussian function to obtain the output of the hidden layer. The competition layer is responsible for connecting the hidden layer units of each class. The number of neurons in this layer is the number of sample classes. The output layer is responsible for outputting the category with the highest score in the competition layer.

The connection between the input layer and the hidden layer is through a Gaussian function to find the degree of matching between each neuron in the hidden layer and each neuron in the input layer. Then accumulate and sum up the matching degree of each category, and then take the average to get the category of the input sample.

3.2. Analysis of simulation results

![Figure 3 Probabilistic neural network test set results](image1)

![Figure 4 Probabilistic neural network test set results of different models](image2)

After processing the steel picture samples with the gray-level co-occurrence matrix, they obtain their own data set and then use the probabilistic neural network for training to obtain the comparison results between 15 different models. The prediction accuracy rate of the probabilistic neural network for the test set is 75%. By comparing different models, it is found that the probabilistic neural network with five characteristic parameters has the highest prediction accuracy on the test set, and the probabilistic neural network training with five characteristic parameters is selected accordingly. The duration is relatively small, and a better classification effect can be achieved.

4. Conclusions

In this paper, a probabilistic neural network is used to classify the sample image data processed by the
gray-level co-occurrence matrix. In the detection process, the speed and accuracy of detection are improved. Therefore, this method provides a new way of thinking for the research field of target classification. Due to the small amount of sample data, the next step is to optimize the sample, and the obtained network model also needs to be further optimized.

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