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Quantitative identification of wire rope based on wavelet super resolution color magnetic flux leakage imaging

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Abstract

In the process of magnetic flux leakage (MFL) detection of wire rope based on unsaturated magnetic excitation(UME), magnetic flux leakage image of defects is extracted from magnetic flux leakage signal, and the present relatively mature image recognition method is used to achieve the purpose of quantitative identification of defects. Therefore, it is an important step in the process of wire rope MFL detection to extract the MFL image of defects from MFL signal. In order to solve the problems of less information in gray images of MFL and low resolution in color images of MFL, this paper proposes a wavelet super resolution color MFL imaging algorithm based on color MFL imaging and wavelet super resolution image reconstruction, which can extract defective super resolution color MFL images from three-dimensional MFL signals. BP neural network classifier was used to carry out the quantitative defect identification experiment of wire rope, and the defect identification effect before and after the proposed algorithm was used to improve the resolution of MFL image was investigated.

Keywords

Wire rope, magnetic flux leakage detection, wavelet super resolution color magnetic flux leakage imaging, quantitative identification.

1. Introduction

Wire rope in coal, transportation, hoisting and many other industries have a wide application, in the use of the process, will inevitably produce wear, broken wire, rust and other damage, these damage will seriously affect production safety, and even endanger personal safety, causing huge economic losses and adverse social impact. Therefore, it is very necessary to study the nondestructive testing of wire rope. Electromagnetic testing method is a widely used nondestructive testing method for wire rope, including magnetic flux leakage(MFL) testing [1,2], eddy current testing [3] and magnetic memory testing [4,5], etc., among which MFL testing has the advantages of easy implementation and low cost, and has been studied and applied more at present. The MFL detection system of wire rope mainly includes MFL signal acquisition and MFL signal processing [6].The main process is that the MFL detection device collects MFL signal on the surface of the wire rope, processes the MFL signal, then identifies the defects, and finally realizes the purpose of quantifying the defects of the wire rope.

In the process of MFL signal processing, the noise reduction processing of MFL signal is carried out first [7], and then quantitative identification research is carried out according to the MFL signal after noise reduction. For the research on quantitative defect identification [8, 9], one method is to directly extract the characteristics of MFL signal of defects and adopt appropriate classification algorithm to carry out quantitative defect identification. In literature [10], the Hilbert transform was used to process the MFL signal, the multi-scale damage index was extracted, and the artificial neural network was used to automatically classify the defects. The

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other is to transform MFL signal into MFL image, which is MFL imaging, and then use appropriate image classification algorithm to quantitatively identify defects. Compared with MFL signal, MFL image is intuitive and easy to understand, with more abundant information and more intuitive expression of defect information. Moreover, MFL image contains more abundant defect information, which can improve the recognition effect of defect classification method. In literature [11], MFL signals were transformed into MFL grayscale images, and the circumferential interpolation method was used to improve the circumferential resolution of the original MFL images. The resolution of MFL grayscale images is relatively low. Therefore, a super resolution reconstruction method based on Tikhonov regularization was proposed in literature [12] to enhance the resolution of MFL grayscale images, and RBF neural network was designed to carry out the broken wire identification experiment. In Literature [13], wavelet super resolution technology was used to improve the resolution of MFL grayscale images, and BP neural network was used to achieve quantitative identification of defects. In literature [14], the image super-resolution algorithm based on interpolation and non-subsampled shearwave transform was adopted to improve the quality of MFL gray-scale images and improve the quantitative identification effect of broken wires. Compared with MFL grayscale images, color MFL images have more abundant information. In literature [15], pseudo-color image enhancement technology was applied to MFL grayscale images to obtain color MFL images, and color features were added as input of BP neural network. Quantitative identification experiments verified that this algorithm could effectively improve the recognition effect. In Literature [16], three-dimensional MFL signals were collected, and the color MFL imaging algorithm was used to obtain the true color MFL images. Compared with the gray images of MFL, the true color MFL images have a higher defect recognition rate.

The main purpose of this paper is to extract the MFL image of the defect from the MFL signal, in order to realize the quantitative identification of the defect by using the relatively mature image recognition methods, and improve the resolution of the MFL image, increase the information content of the image, and improve the recognition effect. In order to solve the problems of less information in gray images of MFL and low resolution in color images of MFL, this paper proposes a wavelet super resolution color MFL imaging algorithm based on color MFL imaging and wavelet super resolution image reconstruction, which can extract defective super resolution color MFL images from three-dimensional MFL signals. BP neural network is a commonly used wire rope defect recognition algorithm [17, 18]. The BP neural network classifier is used to carry out the quantitative defect recognition experiment of wire rope, and the defect recognition effect before and after the proposed algorithm is used to improve the resolution of MFL image is explored.

2. 3D MFL signal acquisition and signal preprocessing

Rope 3d MFL signal acquisition device based on unsaturated magnetic excitation (UME) is used to collect to the 3d MFL signals on the surface of wire rope, device physical diagram as shown in Fig.1. The original 3d MFL signals contain a lot of interference information. To facilitate subsequent defect location and recognition, the original MFL signal is de-noised to filter out a lot of noise, enhance SNR of signal. The color MFL image of the defect is obtained from the three-dimensional MFL signal after de-noising by image processing, and then the features of the MFL image of the defect are extracted, and the extracted features are classified and recognized to get the final result of the defect recognition. The processing process is shown in Fig. 2.

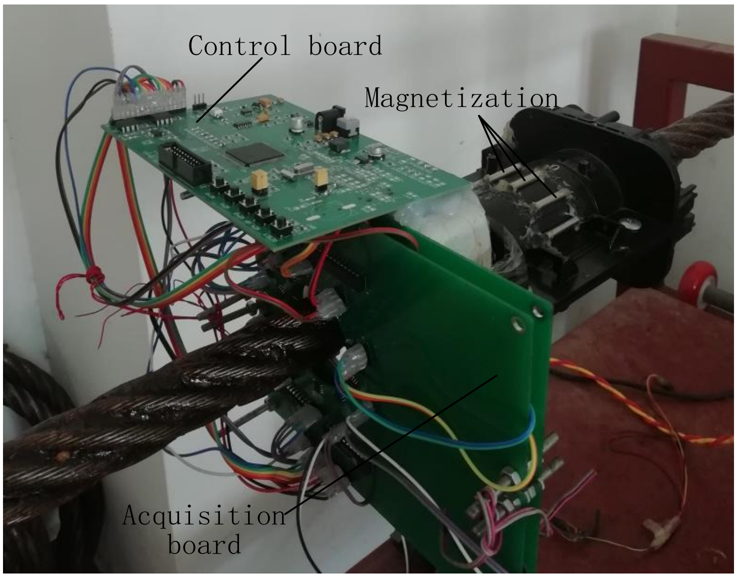


Fig. 1 Physical diagram of the experimental device

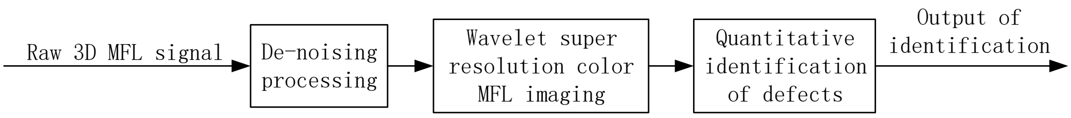
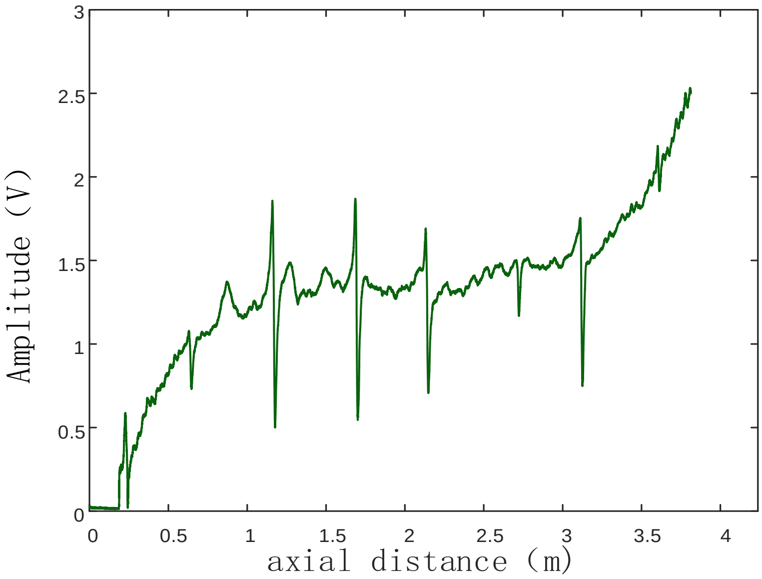
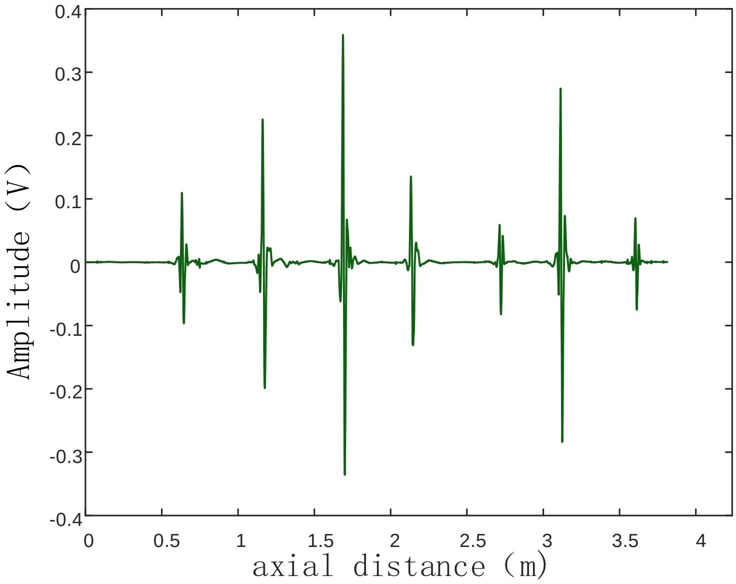


Fig.2 upper computer processing flow

The original data contains a lot of interference noise information, such as electromagnetic pulse noise, magnetic leakage noise between wire rope strands, etc., so the original data should be de-noised and preprocessed first. Radial, tangential and axial MFL signals were de-noised respectively in this paper, and the signals before and after de-noising of one tangential MFL signal are shown in Fig. 3(a) and 3(b) respectively.



(a) Before de-noising



(b)After de-noising

Fig. 3 Tangential MFL signals before and after de-noising

3. Wavelet super resolution color MFL imaging algorithm

Wave super resolution color MFL imaging algorithm is proposed to convert the three-dimensional MFL signal after noise reduction into the super resolution color MFL image of the defect. The main process is as follows:

1) Normalization and circumferential interpolation. In order to facilitate the subsequent processing of MFL data, the MFL signal after noise reduction is normalized first, and the amplitude is normalized to between 0 and 255.MFL signal acquisition device of wire rope, the circumferential distribution 10 sensor channels, 3d MFL data contain radial and tangential and axial component, all have a circumferential resolution of 10, which is far lower than the data sampling rate of axial. So to improve the axial resolution of the radial, tangential and axial MFL data, cubic spline difference is used to increase the axial resolution from 10 to 300;

2) Color MFL imaging. The color imaging method is used to transform the 3D MFL data into color MFL images, and then the defect location and segmentation are carried out to obtain the color MFL images.

3) Defect localization and segmentation. The maximum modulus method is used to locate and segment the defects, and the axial position of the defects and color MFL images are obtained.

4) Wavelet super resolution color image reconstruction. In order to obtain more detailed information of defects and obtain better quantitative recognition effect, the MFL image of defects is processed by using wavelet super resolution color MFL imaging, and finally the super resolution color MFL image of defects is obtained.

Its flow chart is shown in Fig. 4.

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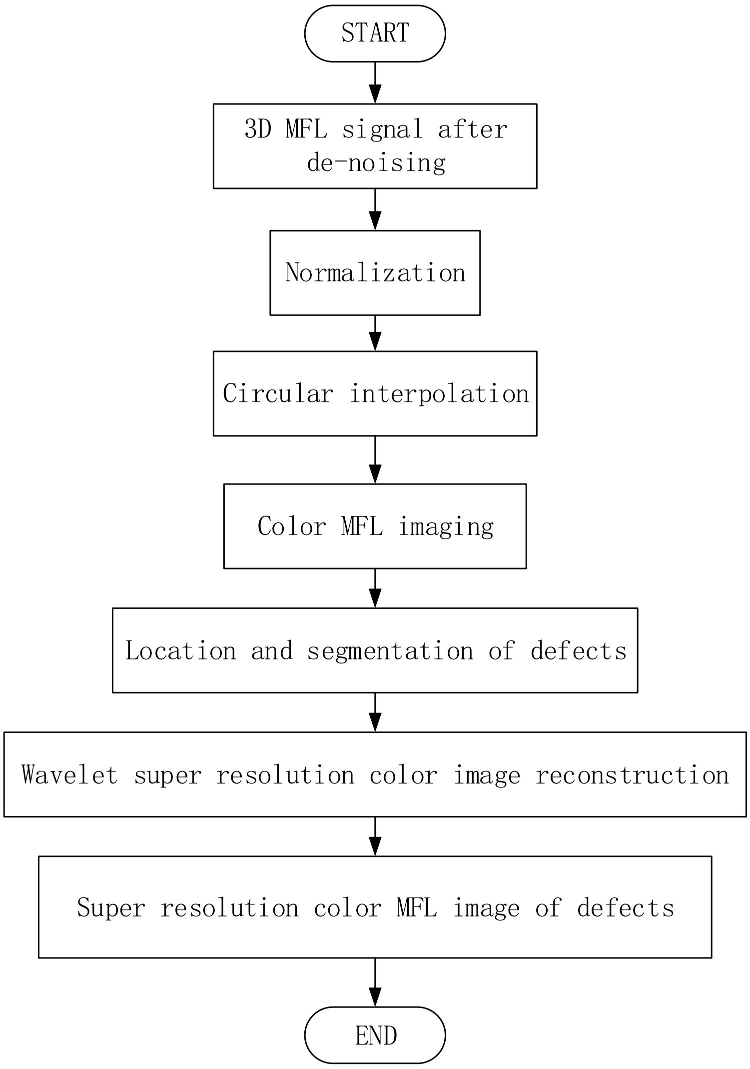

Fig. 4 Color imaging super resolution algorithm flow

3.1. Normalization and interpolation

The normalization of MFL data is the basis of transforming MFL data into MFL images. The way of normalization is the largest minimum normalized, the MFL data normalization to 0 ~ 255 range, according to the formula (1) for normalization, but there are differences in the method for MFL data normalization is not the same as the standard, so using the mean to deal with again to 3 d MFL data background the same standard, facilitate subsequent defect location and recognition, the formula for the formula (2) :

$$h(i)=\frac{x(i)-\min(x(i))}{max(x(i))-\min(x(i))} \tag{1}$$

$$\hat{x}(i)=h(i)-mean\big(h(i)\big)+128 \tag{2}$$

Formula (1), $h(i)$ is the MFL data after normalization, $x(i)$ is the MFL data before normalization, $max\big(x(i)\big)$、 $\min(x(i))$ respectively before the normalized MFL data of the maximum and the minimum; Formula (2), $\hat{x}(i)$ Is the MFL data after de-averaging processing, $mean\big(h(i)\big)$ Is the average value of normalized MFL data.

The circumferential resolution of the collected three-dimensional MFL data of wire rope, namely, the radial, tangential and axial component MFL data, are 10, which is far less than the number of axial sampling points. Therefore, the cubic spline difference is adopted for the radial, tangential and axial MFL data to improve the axial resolution from 10 to 300.

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3.2. Location and segmentation of defects

Grayscale images are monochromatic images, which contain less information. Compared with grayscale images, color images contain more abundant information, which is more conducive to subsequent defect segmentation and recognition. In this paper, the color MFL imaging method is to map the radial, tangential and axial MFL data after interpolation and normalization into three color channels, namely red (R), green (G) and blue (B), to obtain color MFL images. To highlight the defect area, set the weight of the green channel to 0.8 and the weight of the red and blue channels to 1.The MFL grayscale images of radial, tangential and axial MFL data are shown in Fig. 5 (a), 5 (b) and (c), and the color MFL images are shown in Fig. 5 (d).

(a) MFL gray scale image of radial data

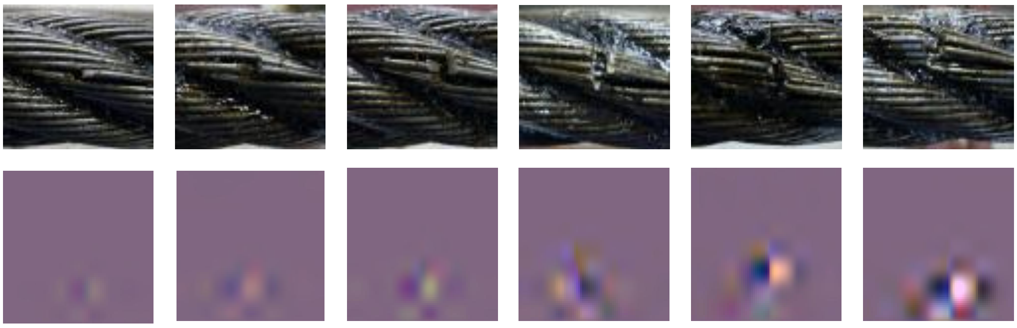
(b)MFL gray scale image of tangential data

(c)MFL gray scale image of axial data

(d)Color image of three-dimensional MFL data

Fig. 5 MFL images

After the color MFL images are obtained from the 3D MFL data, the defects of the color MFL images are located and segmented. Modulus maximum value method is used for defect location and segmentation, the specific process as follows: choose the tangential MFL data, first the circumferential average, the threshold processing, find out the maximum position, get the axial position of the point defects, this point as the center, to the color image of leakage magnetic field forward after the interception of 150 sampling points, the defect of color MFL image can be segmented, resolution of 300 * 300. Fig. 6 shows the physical drawings and color MFL images of six kinds of defects with different number of broken wires. (a), (b), (c), (d), (e) and (f) are respectively 1 broken wire, 2 broken wires, 3 broken wires, 4 broken wires, 5 broken wires and 7 broken wires defects.



(a)1 wire (b)2 wires (c)3 wires (d)4 wires (e)5 wires (f)7 wires

Fig.6 Color MFL images of six defects with different number of broken wires

3.3. Wavelet super resolution color image reconstruction algorithm

The richer the information contained in the MFL image, the better the quantitative identification effect of defects. Therefore, the purpose of this program is to improve the resolution of color MFL images of defects and obtain more abundant information about defects. In this paper, the wavelet super resolution color image reconstruction algorithm is used to process the defect color MFL image, and this algorithm can improve the resolution of color MFL images of defects by twice.

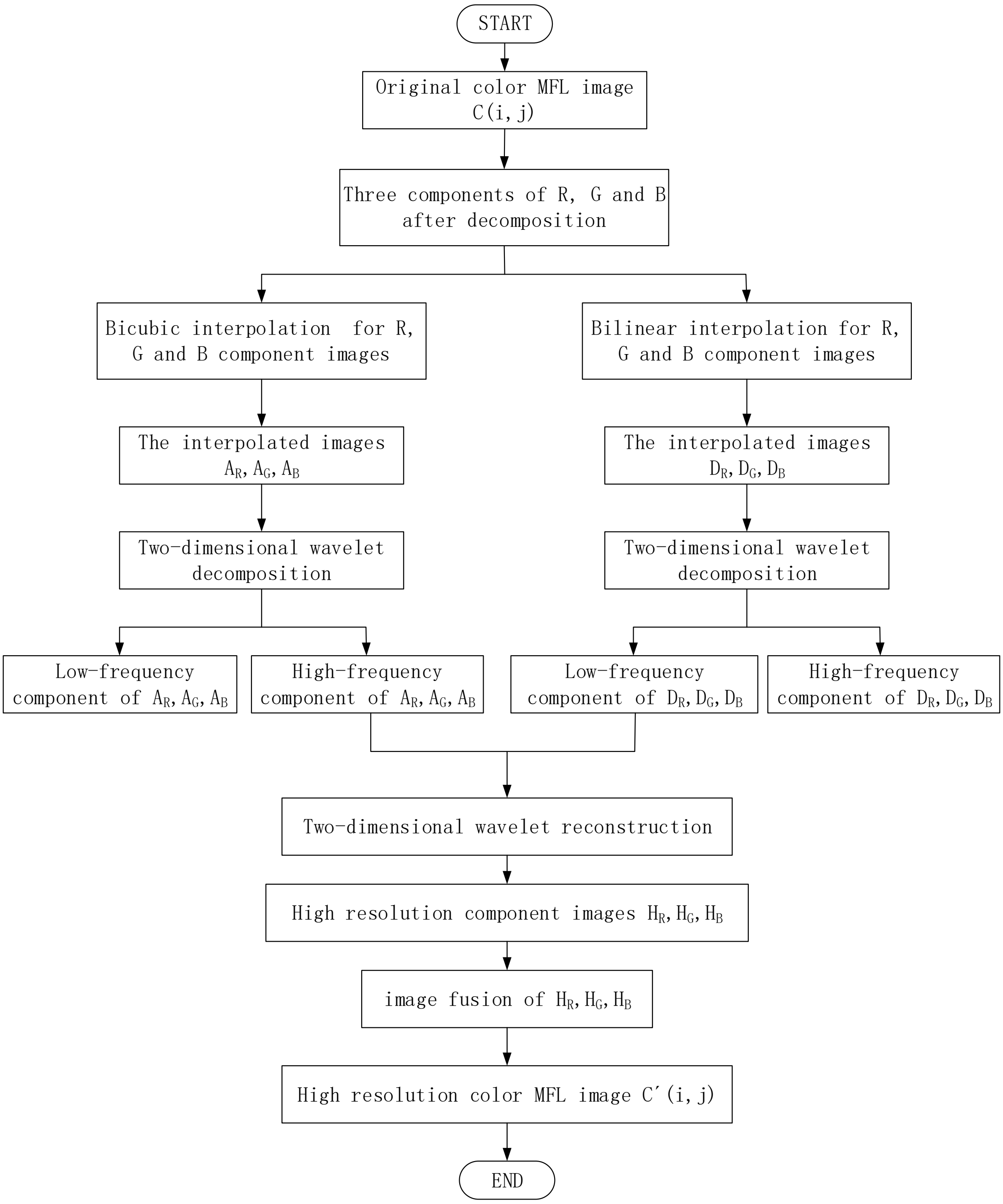


Fig. 7 Wavelet super resolution color image reconstruction algorithm

The basic idea of the wavelet super resolution color image reconstruction algorithm is as follows: a color MFL image can be regarded as a combination of three component images, which is decomposed into three component images; Respectively on the three components of the image super-resolution processing, namely for each component image bilinear interpolation and double three times, increase the overview and detail information component image, then carries on the two-dimensional fast wavelet decomposition, the component of the image of high frequency interpolation and low frequency component, high frequency component represents the image detail information, low frequency component represents the profile image information, so the low frequency component of bilinear interpolation component image and the high frequency component of bicubic interpolation component image are selected for wavelet reconstruction to get three component images of high resolution; After processing the component images, the three high-resolution component images are combined into a color image, which is a high-resolution color MFL image. The detailed process of the algorithm is as follows:

1) A color MFL image is expressed as C(i, j), $C(i,j) = [R(i,j)\ G(i,j)\ B(i,j)]^T$, which is decomposed into three component images of R, G and B;

2) Bicubic interpolation is carried out for the three component images of R, G and B to obtain the interpolated images of A_R, A_G and AB, and bilinear interpolation is carried out for the three component images of R, G and B to obtain the interpolated images of D_R, D_G and D_B.

3) The interpolated image A_R, A_G, A_B and D_R, D_G,D_B are decomposed by two-dimensional fast wavelet to obtain the high-frequency and low-frequency components of the interpolated image;

4) The low-frequency components of bilinear interpolation component images D_R, D_G and D_B and the high-frequency components of bicubic interpolation component images A_R, A_G and A_B are selected for wavelet reconstruction to obtain three high-resolution component images H_R, H_G and H_B.

5) The three components of high resolution image H_R, H_G and H_B are combined into a color image C′(i, j), $C'(i,j) = [H_R(i,j)\ H_G(i,j)\ H_B(i,j)]^T$, which is a subtropical high resolution color MFL image C′(i, j) with resolution of 600 * 600.

Its flow chart is shown in Fig. 7.

Fig. 8 (a) and Fig. 8 (b) are respectively the defect color MFL images before and after processing by the wavelet super resolution color image reconstruction algorithm. After processing, resolution of the defect color MFL image is increased from 300*300 to 600*600, which is doubled.

(a)Before processing (b)After processing

Fig. 8 Before and after processing by the wavelet superresolution color image reconstruction algorithm

4. Quantitative identification of defects

This section is the quantitative identification experiment of wire rope defects to explore the defect recognition rate before and after the improvement of MFL image resolution. BP neural network is used to quantify the defects of wire rope. Firstly, the features of color MFL images of defects are extracted to represent the image information, and the dimension of image information is reduced. The features of color moment features and texture features are extracted from the color MFL images of wire rope defects, which are input of the quantitative identification experiment of wire rope defects. Using BP neural network as classifier, this paper designed the 19 * N * 7 three layers BP neural network, including the input layer and output layer and hidden layer, the input for the extracted 9 color moment and 10 texture features, a total of 19 input, and output layer node number seven, 0 or 1, all nodes in the output of the combination are identified on the number of broken wires. Output layer use logsig function, hidden layer nodes is N, implicit layer use tansig function as transfer function, number of nodes

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in the hidden layer with a lot of training testing, which adopted network training algorithm is trainlm algorithm. The classifier structure of BP neural network is shown in Figure 9:

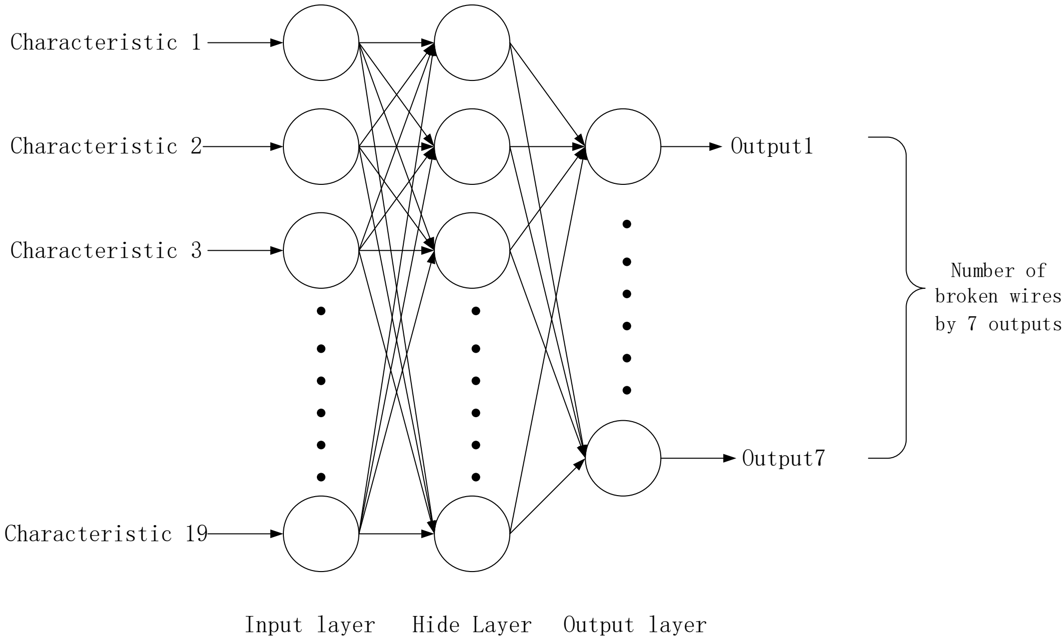

Fig. 9 Structure diagram of classifier of single BP

Broken wire is one of the common damage types of wire rope defects. Quantitative identification of broken wire is one of the main research contents of nondestructive testing of wire rope. The experimental object is a wire rope with a structure of 6*37 and a diameter of 30mm. There are 222 steel wires in total. There were 216 experimental samples, including 41 samples of 1 broken wire defect, 31 samples of 2 broken wire defect, 31 samples of 3 broken wire defect, 32 samples of 4 broken wire defect, 49 samples of 5 broken wire defect and 32 samples of 7 broken wire defect. In the quantitative identification experiment of broken wire of wire rope, the experimental samples are randomly divided into training samples and test samples, with 140 training samples and 76 test samples.

In the analysis of the identification results, the percentage of broken wire is taken as the index to judge the damage of wire rope, and the percentage of broken wire is defined as the percentage of broken wire in the total number of wire rope. The main indicators to judge the experimental identification effect are broken wire identification percentage error e and recognition rate s, and the calculation formulas are Formula (3) and (4), respectively.

$$e = (z' - z)/U \times 100\% \tag{3}$$

$$s = L/M \times 100\% \tag{4}$$

In Formula (3), z' is the predicted result of the number of broken wires in the test samples, z is the actual number of broken wires in the test samples, and U is the total number of steel wires of the wire rope. The structure of the wire rope in this experiment is 6*37, so U is 6*37, namely 222. In Formula (4), L is the number of test samples whose predicted results are the same as the actual results, and M is the total number of test samples, which is 76 in this experiment.

For the original color MFL image with defects and the super resolution color MFL image with wavelet super resolution color MFL imaging algorithm, the recognition results of broken wires by using BP neural network classifier are shown in Fig. 10, where the horizontal axis is the percentage error of broken wire recognition and the vertical axis is the recognition rate.

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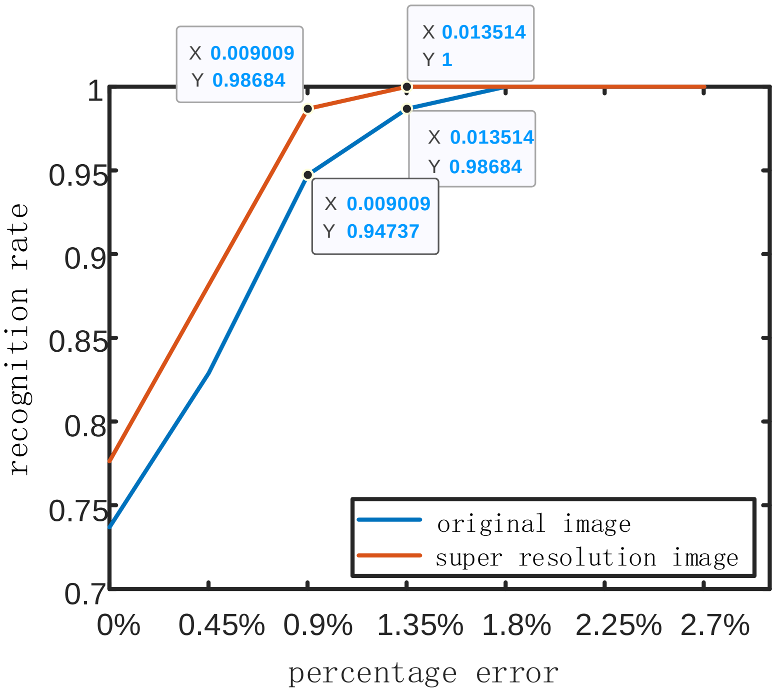

Fig. 10 Broken wire recognition results of original color MFL images and super-resolution color MFL images

The smaller the maximum broken wire identification percentage error is, the closer the number of identified broken wires is to the actual number of broken wires, the better the recognition effect of the model is. The higher the recognition rate is, the more correct samples are identified and the better the model recognition effect is. In the experimental results, the maximum broken wire identification percentage error of the super resolution color MFL image using the wavelet super resolution color MFL imaging algorithm is less than 0.9%, while the maximum broken wire identification percentage error of the original color MFL image is less than 1.35%.When the percentage error of broken wire recognition is 1.35%, the broken wire recognition rate of super resolution color MFL image is 100%, which is higher than 98.684% of MFL image before the resolution is improved. When the percentage error of broken wire recognition is 0.9%, the broken wire recognition rate of super resolution color MFL image is 98.684%, which is higher than that of 94.737% before the resolution is improved. Results analysis shows that the wavelet super resolution color MFL imaging algorithm can improve the resolution of color MFL image, and can effectively improve the quantitative identification effect of broken wire rope.

5. Conclusion

This paper studies the process of obtaining MFL image of defect from the three-dimensional MFL signal. The main content is that a color imaging super resolution algorithm based on color MFL imaging and wavelet super resolution color image reconstruction is adopted to get the super resolution color MFL image of the defect from the three-dimensional MFL signal. The algorithm process includes radial, tangential and axial MFL data normalization and circumferential interpolation, color MFL imaging, defect localization and segmentation, and wavelet super resolution color image reconstruction algorithm. Color MFL imaging algorithm transform 3D MFL data into more intuitive and informative color MFL images. The wavelet super resolution color image reconstruction algorithm proposed in this chapter improves the resolution of MFL image of defects from 300*300 to 600*600, which is doubled, and increases the detailed information of defects. The quantitative identification experiment of wire rope defects was carried out to explore the defect recognition rate before and after the proposed algorithm was used to improve the resolution of MFL image. The analysis of the experimental

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identification results shows that the wavelet super resolution color MFL imaging algorithm could effectively improve the quantitative identification effect of broken wires of wire rope.

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