Research on the Recognition of Surface Defects in Copper Strip Based on Fuzzy Neural Network

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***Abstract*—The quality of copper strips directly affects the performance and quality of copper and its products. So there is great significance to detect and recognize the surface defects in copper strips. The testing results from traditional manual inspection methods are unsatisfactory. So, this paper presents a novel recognition method of surface defects in copper strip based on fuzzy neural network . In this paper, the feature vectors of typical defects picked by the moment invariants form the neural network training samples and fuzzy wavelet neural network based on learning rate dynamically regulated BP algorithm identifies defects . Experiments show that this method can effectively detect surface defects in copper strips in the production line. Besides, it has a high recognition accuracy and speed.**

***Index Terms*—Fuzzy neural network, Copper strips, Identification, Moment invariant**

I. INTRODUCTION

As the development of social productivity and science advancement, the application of copper alloy is more and more wide, and mostly focused on conductor and heat change. It has been indispensable raw materials in several industries such as Power Electronics, automobile industries, shipping, domestic electronics, communications and construction industries. The copper strips surface quality would directly influence the capability and quality of the final products. However, copper strips surface defects inspection is a repetitive and quickly work which needs tremendous concentration. The traditional methods such as artificial visual inspection, strobe light inspection, etc. have the disadvantages such as poor real-time performance, low random inspection ratio, low confidence, harsh environment, etc.

One important characteristic of neural network is the learning ability which obtains the expected input-output mapping through adjusting the self-weight automatically and is available for non-linear issues in pattern recognition. The usually used BP network has a slow training speed and has blindness in topological structure design which is harmful to the further development of neural network, but the usual fuzzy system has no skill at learning and has a low coding precision. Fusion of fuzzy technology and neural network can overcome these disadvantages effectively.

In this paper, first, preprocessing results of defects images were got. Then, feature vectors extracted by improved Hu invariant moments formed the learning sample of fuzzy neural network which had a good performance of defect recognition through training. Wavelet function was used as the fuzzy membership function. The excellently self-learning ability combined excellently local quality of wavelet function enhance the adaptive capability of fuzzy control. Experimental results showed that the network has a high precision of recognition and can detect defects in real-time.

II. FEATURE EXTRACTION

Feature extraction is the key factor which directly decides defects classifier in late stage. In this paper, invariant moments were used to extract features. Moment is a linear characteristic which has invariant characteristics in image rotation, ratio scale and translation. Invariant moment theory based on region shape recognition was proposed by Hu [3] at first. It has been improved in recent years and makes a stronger descriptive ability for invariant characteristics. But it takes much time because all pixels in the image would be computed. Furthermore, chen [4] proposed a fast arithmetic for region invariant moments based on boundary. This paper made some extensions to reference [3] and reference [4] and applied it to copper strips surface defects detection.

The (p+q)th-order general moment and central moment of the two-dimensional density function $f(x, y)$ according to Riemann integral are defined as

$$m_{pq} = \sum\sum x^p y^q f(x,y)$$
$$\mu_{pq} = \sum\sum (x-\bar{x})^p a(y-\bar{y})^q f(x,y) \tag{1}$$

Where $\bar{x} = \frac{m_{10}}{m_{00}}$,$\bar{y} = \frac{m_{01}}{m_{00}}$, and f(x, y) is the gray value of coordinate (x, y).

Then, normalization is applied to central moment, and the result is defined as

$$\eta_{pq} = \frac{\mu_{pq}}{\mu_{00}^r} \tag{2}$$

where $r = (p+q)/2+1, p+q = 2,3,4...$

Hu proposed seven invariant moments which satisfied the conditions of translation invariance, zoomed invariance and

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rotational invariance. These moments can be written

$$\begin{aligned}
\Phi_1 &= \eta_{02} + \eta_{20} \\
\Phi_2 &= (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2 \\
\Phi_3 &= (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2 \\
\Phi_4 &= (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2 \\
\Phi_5 &= (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12})\Phi_x + \\
&\quad (\eta_{03} - 3\eta_{21})(\eta_{21} + \eta_{03})\Phi_y \\
\Phi_6 &= (\eta_{20} - \eta_{02})[\eta_{30} + {\eta_{12}}^2 - \eta_{21} + {\eta_{03}}^2] \\
&\quad +4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03}) \\
\Phi_7 &= (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})\Phi_x \\
&\quad +(3\eta_{30} - \eta_{12})(\eta_{03} + \eta_{21})\Phi_y \\
\Phi_x &= (\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2 \\
\Phi_y &= (\eta_{21} + \eta_{03})^2 - 3(\eta_{30} + \eta_{12})^2
\end{aligned} \tag{3}$$

To quickly compute region invariant moments, chen proposed fast arithmetic based on boundary, of which geometrical moment and central moment are defined as

$$\begin{aligned}
m_{pq} &= \int_c^r x^p y^q f(x,y) ds \\
\mu_{pq} &= \int_c^r (x - \bar{x})^p (y - \bar{y})^q f(x,y) ds
\end{aligned} \tag{4}$$

Where c is a smooth curve, $\bar{x} = \frac{m_{10}}{m_{00}}, \bar{y} = \frac{m_{01}}{m_{00}}$, $\eta_{pq} = \frac{\mu_{pq}}{\mu_{00}^r}$, $r = p + q + 1$,and $p + q = 2, 3, 4 \ldots$.

To make the seven invariant moments proposed by Hu satisfy scaling invariance, we do some transformation:

$$\begin{aligned}
R_1 &= \frac{\sqrt{\Phi_2}}{\Phi_1}, R_2 = \frac{\Phi_1 + \sqrt{\Phi_2}}{\Phi_1 - \sqrt{\Phi_2}}, R_3 = \frac{\sqrt{\Phi_3}}{\sqrt{\Phi_4}}, \\
R_4 &= \frac{\sqrt{\Phi_3}}{\sqrt{|\Phi_5|}}, R_5 = \frac{\sqrt{\Phi_4}}{\sqrt{|\Phi_5|}}, R_6 = \frac{|\Phi_6|}{\Phi_1} * \Phi_3, \\
R_7 &= \frac{|\Phi_6|}{\Phi_1 * \sqrt{|\Phi_5|}}, R_8 = \frac{|\Phi_6|}{\Phi_3 * \sqrt{|\Phi_2|}}, \\
R_9 &= \frac{|\Phi_6|}{\sqrt{\Phi_2 * |\Phi_5|}}, R_{10} = \frac{|\Phi_5|}{\Phi_3 * \Phi_4}
\end{aligned} \tag{5}$$

Reference [4] has proved that $R_1, R_2, \ldots R_{10}$ can satisfy the translation invariance, scaling invariance and rotational invariance. It got a new secular equation to describe shape based on the extension of Hu invariant moments.

III. FUZZY NEURAL NETWORK

Wavelet analysis has been widely used in signal processing filed for a good local quality in time-frequency domain and identical resolution [13]. In this paper, we used wavelet function as fuzzy membership function.

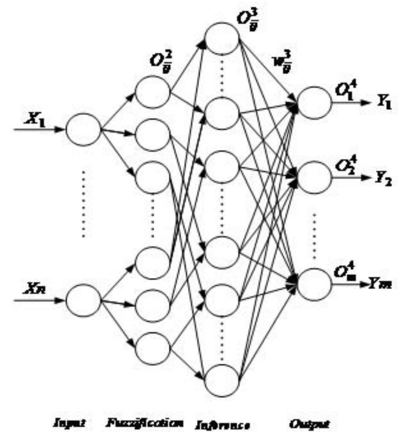

Fig. 1. The Structure of Fuzzy Wavelet Neural Network

A. wavelet function

if $\Psi(t) \in L^2(R)$, and the corresponding Fourier transform is $\Psi(\omega)$, when $\Psi(\omega)$ meets the follow condition

$$\begin{aligned}
C_\Psi &= \int_{-\infty}^{+\infty} |\omega|^{-1} |\Psi(\omega)| d\omega \leq \infty \\
&Or \int_{-\infty}^{+\infty} \psi(t) dt = 0,
\end{aligned} \tag{6}$$

then, $\Psi(\omega)$is called base wavelet or mother wavelet. Wavelet sequence is gotten through scaling and translation transform of $\psi(t)$.

We define $\psi_{a,b}(t)$ as

$$\psi_{a,b}(t) = a^{-\frac{1}{2}} \psi(\frac{t-b}{a}), a, b \in R; a \geq 0 \tag{7}$$

which is the sequential wavelet depend on a,b generated by mother wavelet ψ. For any $f(t) \in L^2(R)$, wavelet transform is defined as

$$\begin{aligned}
WT_f(a,b) &= < f(t), \psi_{a,b}(t) > \\
&= a^{-\frac{1}{2}} \int_{-\infty}^{+\infty} f(t) \psi^*(\frac{(t-b)}{a}) dt
\end{aligned} \tag{8}$$

where $\psi_{a,b}(t)$is the displacement and scale of base wavelet, $a \geq 0$ is scale factor; b is displacement with a positive or negative value.

For any $f(t) \in L^2(R)$, f(t) can be reconstructed by wavelet coefficients:

$$f(t) = \frac{1}{C_\Psi} \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} WT_f(a,b) \psi_{a,b}(t) \frac{1}{a^2} da db \tag{9}$$

In this paper, we used base wavelet function as fuzzy membership function which is given by

$$\psi(x) = cos(0.25x) \cdot exp(-x^2/2) \tag{10}$$

B. fuzzy wavelet neural network

The structure of fuzzy wavelet neural network [5], [6], [9] is shown in Fig 1, including input layer, fuzzification layer, fuzzy reasoning layer and output layer.

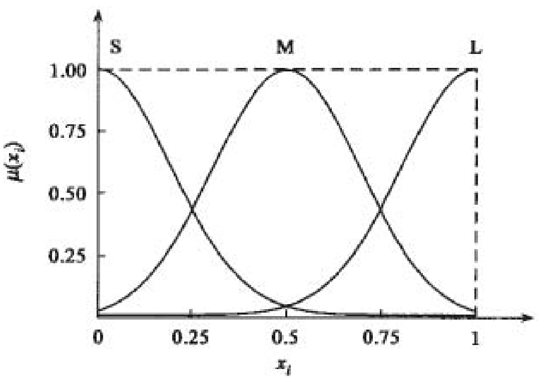

Fig. 2. The curve of Fuzzy Membership Function

(1)The feature vectors extracted by improved Hu invariant moments form the input of neural network and each input is normalized to [0,1]. The output is

$O_i^1 = l_i^1 = x_i, (i = 1, 2, \ldots, n)$

(2)Fuzzification layer finishes the fuzzification of input feature vectors. This paper used 3 fuzzy subsets. The subordination of input x_i and the j-th is defined as

$\mu_{i,j}(x_i) = \psi_{a_{ij},b_{ij}}(x_i) = cos(0.25 \cdot \frac{x_i - b_{ij}}{a_{ij}}) \cdot [-\frac{(x_i - b_{ij})^2}{2a_{ij}^2}]$
$i = 1, 2, \ldots, n; j = 1, 2, 3;$

Where a_{ij} are scaling factors and b_{ij} are shift factors. Fig 2 shows the curve of fuzzy membership function.

The output is

$I_{ij}^2 = O_i^1;$

$O_{ij}^2 = \mu_{ij}(I_{ij}^2) = cos(0.25 \cdot \frac{O_i^1 - b_{ij}}{a_{ij}}) \cdot exp[-\frac{O_i^1 - b_{ij}{}^2}{2a_{ij}^2}],$
$(i = 1, 2, \ldots, n; j = 1, 2, 3)$

(3)Fuzzy reasoning layer takes comprehensive measurements in fuzzy feature vectors. The coefficients of connection between the second-layer and third-layer nodes are $w_{ij}^2 = 1$. The output is

$O_{ij}^3 = I_{ij}^3 = min(O_{1j}^2, O_{2j}^2, \ldots, O_{nj}^2)(j = 1, 2, 3)$

(4)The output layer implements fuzzification. The output function is

$I_k^4 = \sum_{i,j=1}^3 O_{ij}^3 \omega_{ij}^3 Y_k = O_k^4 = \frac{I_k^4}{\sum_{i,j=1}^3 O_{ij}^3}$
$(k = 1, 2, \ldots, m)$

Where w_{ij}^3 are the connection weights of the networks and Y_k are the output of the network.

C. networks training scheme

The ith defect feature vector is used as the input of training sample and the expected output is numbered i. The feature vectors form the input to fuzzy neural network, recognition results are given by the output of the neural network.

The traditional BP algorithm is a descending gradient, whose learning rate is the step length of descending gradient which stays the same during the whole training time. The capability of the learning is sensitive with the learning rate, a large learning rate may occurred oscillation and instability; the algorithm has a low convergence and a long training time if the learning rate is too small. Also, it is unpractical to chose a best learning rate before training.

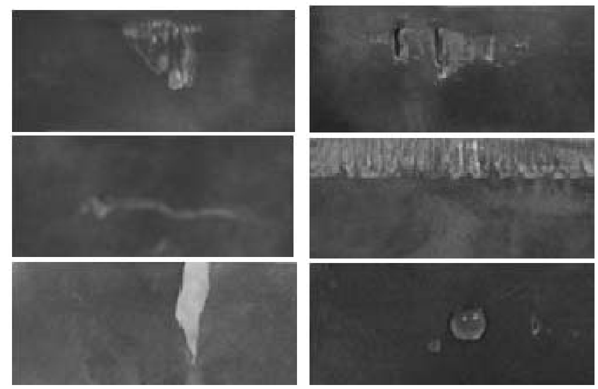

Fig. 3. Typical defects image of copper strips (a)pit (b)holes (c)scratch (d)burrs (e)indentation (f)smearing

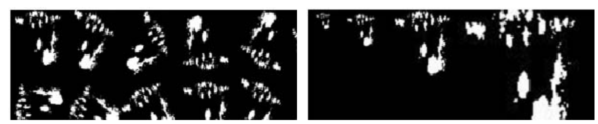

Fig. 4. (a) Learning sample images of pit defect after rotation transformation (b) Learning sample images of pit defect in different resolution

In this paper, we used a novel BP algorithm which dynamically regulated the learning rate. The modified formula is

$$\eta(K+1) = \eta(K) - \tau \frac{\triangle E}{E} 0 \leq \tau \leq 1 \quad (11)$$

Where $\eta(K+1)$ is the learning rate of all sample by the K+1th step.

$\eta(K)$is the learning rate of all sample by the Kth step.

$\tau$is a constant. $\frac{\triangle E}{E}$is error change rate.

The rate of error change is computed each time as all samples finish a learning cycle.

$$\frac{\triangle E}{E} = \frac{E(K) - E(K-1)}{E(K)} \quad (12)$$

Where $E(K)$ is the global error of all samples by the Kth step; and $E(K+1)$ the K+1th step.

When $\triangle E \geq 0$,the learning error is increasing, the output is far away the expected value, $\triangle W$ need to be reduced, and the reduction of η will make a quick convergence. While $\triangle E \leq 0$,the learning error is reducing, the output is approaching the expected value, $\triangle W$ need to be increased. But the error is small which makes little effect to $\triangle W$ and makes slow convergence, just as the change of $\frac{\triangle E}{E}$ is more larger, so η increased clearly which can make a quick convergence.

IV. SIMULATION AND RESULTS ANALYSIS

Fig 3 shows defects image collected from copper strips factory including six typical defects of copper strips. Because copper strip reflects light and has complicated defects, we segmented image captured by CCD, got the binary image and built a database for typical defects. To build a complete database, we rotated the image and transform it in different resolutions.

TABLE I
TESTING RESULTS

predict	pits	holes	scratches	burrs	smearing
total	126	342	215	332	106
true	112	323	203	319	232
accuracy	88.9%	94.4%	94.4%	96.1%	90.6%

TABLE II
BP ALGORITHM PERFORMANCE

algorithm	improved BP	traditional BP
control accuracy	0.001	0.001
iteration	5102	7236
time	113s	251s
average error	0.0163	0.0615

(1)Rotation.

Rotating the typical defect image every 30 degrees. Fig4(a) shows the rotational images.

(2)Transformation in different resolutions.

Transforming the pits image in 64×64, 128×128, 256×256, 512×512 resolutions. Fig4(b) shows the processed images.

288 images through rotation, resolution transform and fuzzy process are used as the training samples of fuzzy wavelet neural network. The experimental results are shown in table I.

In this paper, we used a novel BP algorithm with dynamically regulated learning rate.To test the performance of the improved RBF neural network using the new BP algorithm, we compare the capability of traditional BP algorithm and improved BP algorithm. The performance of traditional BP algorithm and the improved BP algorithm is shown in table II. Experiment showed that this method took less time than the traditional BP algorithm.

V. CONCLUSIONS

In this paper, we used RBF neural network as the defect classifier. Moment invariant has been used as the eigenvectors of the defects image.The experiments showed that wavelet fuzzy neural network can detect the surface defects of copper strips at a high accuracy which can meet the requirements of real-time, effectiveness in copper strips rolling. It is important to guarantee the quality of copper strips.

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