

Fabric Defect Classification Using Wavelet Frames and Minimum Classification Error Training

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Abstract—This paper proposes a new method for fabric defect classification by incorporating the design of a wavelet frames based feature extractor with the design of an Euclidean distance based classifier. Channel variances at the outputs of the wavelet frame decomposition are used to characterize each nonoverlapping window of the fabric image. A feature extractor using linear transformation matrix is further employed to extract the classification-oriented features. With an Euclidean distance based classifier, each nonoverlapping window of the fabric image is then assigned to its corresponding category. Minimization of the classification error is achieved by incorporating the design of the feature extractor with the design of the classifier based on Minimum Classification Error (MCE) training method. The proposed method has been evaluated on the classification of 329 defect samples containing nine classes of fabric defects, and 328 nondefect samples, where 93.1% classification accuracy has been achieved.

Keywords—Fabric inspection, defect classification, wavelet frames, minimum classification error

I. INTRODUCTION

Fabric Automatic Visual Inspection (FAVI) is becoming an attractive alternative to human vision inspection in modern textile industry. Based on the advances in image processing and pattern recognition, FAVI can potentially provide an objective and reliable evaluation on the fabric production quality. Most FAVI systems claims to be able to detect the presence of defects in fabric products, and precisely locate the defects. Moreover, classification of fabric defects to their original categories is also highly desired. The motivations behind the classification of fabric defect lie in the facts that the cause and effect of fabric defects are different from class to class. Based on fabric defect classification, the statistics of the occurrence of each type of defects can be obtained. According to the cause of each type of defects, the statistics may indicate malfunctions in certain components of the weaving machine, and enable on-line quality control of the weaving process. Referring to the effect (severity) of each type of defects, the statistics provide necessary information for the grading of fabric product, and give rise to appropriate actions on fabric product. Compared to fabric defect detection, which has already been commercially available, the classification of

fabric defect is much more complex and still remains a research topic presently. The major obstacles in defect classification include [1]:

- Enormous data throughout in the processing of fabric images, especially in on line fabric inspection.
- Large number of defect classes.
- Same class of defects may take different appearances in different factories and different fabric materials.
- The diversity within each class of defects and the similarities among different classes of defects.
- The changes in the weaving process may result in new classes of fabric defects.

Previous works on defect classification can be divided into two categories. In the first category, defects are classified in terms of their shape characteristics [1,2]. From the cortical projection of the material image, Brzakovic et al. [1] extracted shape features of defect (roundness, orientation and overall shape) for the classification of defects in uniform web materials. Based on the detected defect region, Bradshaw [2] calculated the size and width-to-height ratio of the defect region to classify the defects in knitted fabric. The shape characteristics is useful for a rough classification of defects, e.g., horizontal defects, vertical defects and area defects. However, they are not able to provide enough discrimination to classify defects into their original categories. The second category is based on texture analysis. The fabric image has regular periodic texture pattern produced during manufacturing, while different classes of fabric defects locally cause different types of texture. Hence, the classification of defects can be formulated as a texture classification problem. To achieve that, autocorrelation function [3], local integration [4] and gray level difference method [5] have been used to extract statistical texture features for defect classification.

In this paper, a new method based on texture analysis approach is proposed for classifying fabric defects into their original categories. Wavelet frame decomposition [6] is employed to characterize the texture property of a fabric image at multiscale and multiorientation. Compared to the single-scale statistical texture features, channel variances at the output of the wavelet frame decomposition are able to

provide more efficient discriminations among different class of defective fabric textures. Based on the recent development of a discriminative training method known as Minimum Classification Error (MCE) training [7], a feature extractor is designed in conjunction with the design of a classifier in a consistent way for minimizing the error rate in defect classification. The efficiency of this design strategy has been demonstrated in speech recognition [8,9,10] and optical character recognition [11,12]. Traditionally, the design of the feature extractor and the classifier in a defect classification system are loosely linked, which may not yield appropriate interactions between the feature extractor and the classifier. By using the MCE training based design strategy, features which are more suitable for the classifier are extracted and the inconsistency between the feature extractor and the classifier is alleviated. Consequently, better performance can be achieved in defect classification. The proposed fabric defect classification method has been evaluated on the classification of 329 defect samples containing nine classes of defects and 328 nondefect samples, where 93.1% classification accuracy has been achieved.

This paper is organized as follows. In the next section, the proposed defect classification method is presented. The feature extraction module and classification module in the defect classification are first described. Then we describe how to incorporate the design of the feature extractor with the design of the classifier parameters by using MCE training method, for achieving the objective of minimum error rate in the defect classification. The evaluation results of the proposed method are reported in Section 3. Section 4 concludes this paper.

II. FABRIC DEFECT CLASSIFICATION USING WAVELET FRAMES AND MCE TRAINING

Fig. 1 illustrates the block diagram of the proposed fabric defect classification method. The defect classification consists of a feature extraction module and a classification module. In the feature extraction module, feature vectors consisting of channel variances at the outputs of the wavelet frame decomposition are extracted to characterize each nonoverlapping window of the fabric image. A feature extractor, which is implemented by using a linear feature transformation matrix, is then employed to extract suitable wavelet features for the classification of defect. In the classification module, an Euclidean distance based classifier is used. Minimization of the classification error is achieved by using the MCE training method, which is illustrated in Fig. 1 using dashed lines. In the MCE based design framework, defect classification on a set of training images is evaluated by using a loss value that is consistent with the classification error probability. The loss value is then minimized by the design of the feature extractor in the feature extraction module and the design of the classifier parameters in the classification module.

A. Feature Extraction Based on Wavelet Frame Decomposition

Fig. 2 illustrates the filter bank implementation of 2-dimensional wavelet frame decomposition, where $H(z)$ and $G(z)$ denote the z-transform of the low-pass filter $h[n]$ and high-pass filter $g[n]$ respectively. $I(x,y)$ denotes an image and (x,y) is the spatial indices. $\{W_r^1(x,y), W_r^2(x,y), W_r^3(x,y)\}$ denote the wavelet coefficients at scale r , with diagonal, horizontal and vertical orientation respectively, and $R_r(x,y)$ represents the residue signal at scale r .

The fabric image is divided into nonoverlapping windows with size $N_w \times N_w$, and the defect classification is performed on each image window. To characterize each image window, channel variances [6] at the outputs of the wavelet frame decomposition are used. As it is shown in [6], channel variances are able to provide efficient discriminations among different types of textures. Therefore, these features are employed here for the discrimination of different classes of defective fabric textures and the nondefect fabric texture. Corresponding to a window in the fabric image, the channel variances are estimated as the mean energy of the wavelet coefficients in the window

$$w_r^d = \underset{(x,y) \in \text{window}}{\text{Mean}} [W_r^d(x,y)]^2, \quad \text{for } d=1,2,3. \quad (1)$$

The channel variances at each channel of the wavelet frame decomposition form a D-dimensional feature vector to characterize the image window

$$\mathbf{F} = [w_1^1, w_1^2, w_1^3, \dots, w_I^1, w_I^2, w_I^3], \quad (2)$$

where I is the depth of the wavelet frame decomposition, and D is equal to $3I$.

In general, the feature representation of the raw wavelet features \mathbf{F} may not be appropriate for the classification. Therefore, a feature extractor is further employed to extract salient features of each class from the raw wavelet features \mathbf{F} . For simplicity, a $D \times D$ linear transformation matrix $\mathbf{U} = \{U_{ij}\}_{1 \leq i,j \leq D}$ is used as the feature extractor, which yields a new feature vector $\mathbf{V} = \mathbf{U}\mathbf{F}$.

B. Classification Algorithm

Based on the Euclidean distance similarity measure, the discriminant function $g_l(\mathbf{F}, \mathbf{T})$ for class C_l is given as follows.

$$g_l(\mathbf{F}; \mathbf{T}) = \|\mathbf{V} - \mathbf{m}_l\|^2 = \sum_{i=1}^D (V_i - m_{li})^2 = \sum_{i=1}^D \left(\sum_{j=1}^D U_{ij} F_j - m_{li} \right)^2, \quad (3)$$

for $l=1, \dots, J$,

where $l=1, \dots, J-1$ denotes $J-1$ classes of defects and $l=J$ denotes the nondefect class. $\Lambda = \{\mathbf{m}_l\}_{l=1, \dots, J}$ are the reference vectors representing each class, and $\mathbf{T} = \{\mathbf{U}, \Lambda\}$ denotes the trainable parameters in the feature extractor and the classifier. V_i, m_{li} ,

and F_j represent the i^{th} and j^{th} component of \mathbf{V} , \mathbf{m}_l and \mathbf{F} respectively.

The decision rule of the classifier is

$$\mathbf{F} \in C_q \quad \text{if} \quad q = \underset{l}{\operatorname{arg\,min}} g_l(\mathbf{F}; \mathbf{T}). \quad (4)$$

That is, an image window with feature vector \mathbf{F} is classified as class q if the discriminant function $g_q(\mathbf{F}, \mathbf{T})$ is the smallest among all the classes.

C. The Design of the Feature Extractor and the Classifier using MCE Training

A discriminative training method, called Minimum Classification Error (MCE) training method, has been proposed by Juang and Katagiri [7] for the design of the classifier. Since the decision rule for classification is directly incorporated into the objective criterion in MCE training, the classifier is trained in a manner which is more consistent with the objective of minimum classification error rate than the traditional training methods. To achieve appropriate interactions between the front-end feature extractor and the back-end classifier, A. Biem et al. [9] and H. Watanabe et al. [10] further extended the MCE training method from the back-end classifier to the front-end feature extractor for the design of the overall pattern recognizer. In our approach, MCE based design strategy is used to jointly design the feature extractor and the classifier, such that error rate in the defect classification is minimized. In the defect classification shown in Fig. 1, the adjustable parameters of the feature extractor are the transformation matrix \mathbf{U} , and the adjustable parameters of the Euclidean distance based classifier are the reference vectors $\mathbf{\Lambda}$. The total set of adjustable parameters in the defect classification is $\mathbf{T}=\{\mathbf{U}, \mathbf{\Lambda}\}$. MCE training on the parameter set $\mathbf{T}=\{\mathbf{U}, \mathbf{\Lambda}\}$ is implemented as follows [7, 8].

Given a set of N training samples $\mathbf{\Gamma}=\{\mathbf{F}^{(n)}\}_{n=1, \dots, N}$ where the class of each sample is labeled, a misclassification measure d_n [13] is defined for each training sample $\mathbf{F}^{(n)}$ as

$$d_n = 1 - \frac{\left[\frac{1}{J-1} \sum_{p \neq q} g_p(\mathbf{F}^{(n)}; \mathbf{T})^{-\eta} \right]^{-1/\eta}}{g_q(\mathbf{F}^{(n)}; \mathbf{T})}, \quad \text{for } \mathbf{F}^{(n)} \in C_q, \quad (5)$$

where η is a positive number which controls the contributions of the competing classes. When η approaches ∞ , the misclassification measure becomes

$$d_n = 1 - \frac{g_{p_{\min}}(\mathbf{F}^{(n)}; \mathbf{T})}{g_q(\mathbf{F}^{(n)}; \mathbf{T})}, \quad (6)$$

where

$$g_{p_{\min}}(\mathbf{F}^{(n)}; \mathbf{T}) = \underset{p, p \neq q}{\operatorname{arg\,min}} g_p(\mathbf{F}^{(n)}; \mathbf{T}). \quad (7)$$

According to the classification decision rule defined in (4), $d_n \leq 0$ indicates a correct classification while $d_n > 0$ indicates otherwise. By incorporating the decision rule in this misclassification measure, d_n enumerates how likely the sample $\mathbf{F}^{(n)}$ is misclassified.

Based on the misclassification measure, a loss function is then used to evaluate the classification performance on training sample $\mathbf{F}^{(n)}$. The loss function is defined as the smoothed zero-one function of the misclassification measure

$$l_n = \frac{1}{1 + e^{-\alpha d_n}}, \quad (8)$$

where $\alpha > 0$. For the total set of training samples $\mathbf{\Gamma}$, the empirical average cost is defined as

$$L = \frac{1}{N} \sum_{n=1}^N l_n. \quad (9)$$

By minimizing this empirical average cost with respect to the set of parameters $\mathbf{T}=\{\mathbf{U}, \mathbf{\Lambda}\}$, both the feature extractor and the classifier are designed for the minimum error rate in the defect classification. The steepest gradient descent algorithm is normally employed by the MCE training to minimize the empirical average cost. To perform the optimization more efficiently, Quasi-Newton optimization method [14] is used instead. The calculation of the gradient of the empirical average cost L with respect to the parameter set $\mathbf{T}=\{\mathbf{U}, \mathbf{\Lambda}\}$, as required by the Quasi-Newton method, is given as follows:

$$\frac{\partial L}{\partial U_{ij}} = \frac{1}{N} \sum_{n=1}^N \frac{\partial l_n}{\partial U_{ij}} = \frac{1}{N} \frac{\alpha e^{-\alpha d_n}}{[1 + e^{-\alpha d_n}]^2} \sum_{n=1}^N \frac{\partial d_n}{\partial U_{ij}}, \quad (10)$$

$$\frac{\partial L}{\partial \mathbf{m}_l} = \frac{1}{N} \frac{\alpha e^{-\alpha d_n}}{[1 + e^{-\alpha d_n}]^2} \sum_{n=1}^N \frac{\partial d_n}{\partial \mathbf{m}_l}, \quad (11)$$

where

$$\frac{\partial d_n}{\partial U_{ij}} = \frac{2 \left[\frac{1}{J-1} \sum_{p \neq q} g_p(\mathbf{F}^{(n)}; \mathbf{T})^{-\eta} \right]^{-1/\eta}}{g_q(\mathbf{F}^{(n)}; \mathbf{T})} \cdot \left[\frac{(V_i^{(n)} - m_{qi})}{g_q(\mathbf{F}^{(n)}; \mathbf{T})} - \frac{\sum_{p \neq q} g_p(\mathbf{F}^{(n)}; \mathbf{T})^{-\eta-1} (V_i^{(n)} - m_{pi})}{\sum_{p \neq q} g_p(\mathbf{F}^{(n)}; \mathbf{T})^{-\eta}} \right] \cdot F_j^{(n)}. \quad (12)$$

$$\frac{\partial d_n}{\partial \mathbf{m}_l} = \begin{cases} \frac{2 \left\{ \frac{1}{J-1} \sum_{p,p \neq q} g_p^{-\eta} \right\}^{-1/\eta}}{g_q^2} (\mathbf{m}_l - \mathbf{V}^{(n)}) & l = q \\ \frac{2 \left\{ \frac{1}{J-1} \sum_{p,p \neq q} g_p^{-\eta} \right\}^{-1/\eta-1}}{g_q} g_p^{-\eta-1} (\mathbf{m}_l - \mathbf{V}^{(n)}) & l \neq q \end{cases} \quad (13)$$

III. EVALUATIONS

A. Data Collection

The proposed defect classification method has been evaluated on the classification of nine types of typical fabric defects on plain, twill fabrics, as shown in Fig. 3. Fabric without defect should be classified into the nondefect class. Totally eighty-three fabric images containing nine types of defects were used for the evaluation. Feature vectors were extracted to characterize the nonoverlapping image windows of size 32x32 pixels. Forty-two fabric images were used for training, where 336 defect samples and 336 nondefect samples were collected. The remaining forty-one fabric images were used for test, where 329 defect samples and 328 nondefect samples were collected.

B. Evaluation Conditions

1) The selection of the wavelet basis

In wavelet frame decomposition, the selection of the wavelet basis determines the wavelet filters $H(z)$ and $G(z)$. In our evaluation, Haar wavelet basis is selected since it yields wavelet coefficients with good spacial localization. This property was shown to be closely relevant to texture classification [6].

2) Decomposition depth of the wavelet transform

When the decomposition depth of the wavelet transform is increased, the feature vector \mathbf{F} includes more features which are extracted from the channels at the increased scales of the wavelet transform. In our evaluation, wavelet transform with decomposition depth 3 were investigated, where 3 scales features (9 features) of the wavelet transform were used for defect classification.

3) The selection of η and α in the MCE training

In the definition of the misclassification measure d_n , η controls the contributions of the competing classes. In the definition of the loss function l_n , α controls the loss value of the training sample. To evaluate the impact of η and α on the performance of the classification method, different η and α were used in the MCE training, and the corresponding classification performance are illustrated in Fig. 4. As shown in Fig. 4, α of value 5 always yields better classification performance than α with other values when η is greater than 1. The best performance is obtained when α and η equal to 5 and 10 respectively.

4) The effect of using different window size

The wavelet features are calculated in each nonoverlapping window of the fabric image. As a result, the size of the window affects the discriminating power of the wavelet feature in the classification of defects. A suitable window size should well preserve the texture property of defective fabric textures and the nondefect fabric texture. Obviously, the selection of window size is determined by the resolution of the fabric image. Based on our fabric images, MCE training was performed on image windows with size 16x16, 32x32 and 64x64 respectively. The corresponding classification accuracy of the test samples are summarized in Table I. The results shown in Table I indicate that window of size 32x32 is a suitable choice.

5) Initialization in the MCE training

Since the implementation of MCE is based on gradient descent optimization (Quasi-Newton method), the performance of the classification method using MCE training depends on the initialization of the parameter set $\mathbf{T}=\{\mathbf{U},\mathbf{\Lambda}\}$. The transformation matrix \mathbf{U} was initialized using an identity matrix. \mathbf{U} is then fixed and the MCE training is performed to initialize the reference vectors $\mathbf{\Lambda}$ of the classifier. That is, corresponding to the initial feature extractor, the classifier parameters were initialized for the minimum error rate in the classification. The MCE training on the classifier also needed reasonable initialization on $\mathbf{\Lambda}$, which was implemented by maximum likelihood method (using class-dependent mean vectors).

C. Evaluation Results

The MCE training procedure for the design of the feature extractor and the classifier is divided into three steps. At each step, the classification performance is evaluated.

Step 1: Initialization of the transformation matrix \mathbf{U} with identity matrix. The reference vectors $\mathbf{\Lambda}$ of the classifier are obtained by using maximum likelihood method, where the reference vector for each class is calculated as the class-dependent mean vectors.

Step 2: MCE training on the reference vectors $\mathbf{\Lambda}$.

Step 3: MCE training on $\mathbf{T}=\{\mathbf{U},\mathbf{\Lambda}\}$.

Learning curves of the MCE training is illustrated in Fig. 5. At each step of the training, classification rates of training samples and test samples are summarized in Table II. In step 1, the poor classification performance indicates that the reference vectors estimated using the class-dependent mean vectors cause large decision bias. In step 2, the decision bias caused by the estimation of the classifier parameters $\mathbf{\Lambda}$ was alleviated by using MCE training, which resulted in a 19.1% improvement in the classification of test samples. In step 3, both the feature extractor and the classifier were designed by using the MCE training method for the objective of minimum error rate. This design method extracts classification-oriented features and yields appropriate interactions between the feature extractor and the classifier, which further achieves a 8.1% improvement in the classification of test samples.

Corresponding to the overall classification rate of 93.1%, detailed classification performances on each class of defect and the nondefect class are summarized in Table III. It can be observed that the performance on the classification of Wrong Draw is poor. This is due to the weak wavelet response of this defect. Improvements to the results can be obtained by specially designing a wavelet basis [15] for Wrong Draw. Also, wavelet packet frames [16] can be used for feature extraction to enhance the performance on Wrong Draw. Using the designed feature extractor and classifier, Fig. 6 illustrates the classification results of the fabric images shown in Fig. 3. In Fig. 6, dark region denotes the image windows which are correctly classified. Grey region denotes these image windows that are falsely classified into the indexed defective classes, and white region denotes the image windows classified as nondefect class. Note that, in the classification of defect ThinBar Type B, the boundary of the defect region is classified as ThinBar, which is due to the similarity of these two classes of defects.

In comparison with results by other researchers, Brzakovic et al. [1] gave a classification accuracy of 85% for uniform web material inspection. The same classification accuracy was given by Bradshaw [2] in his classification of defects into four categories: vertical, horizontal, local and slubs. Tolba et al. [3] reported on a 100% accuracy, but the result was based on classification into only three categories (vertical, horizontal and area defects). Also, only 22 test samples were used. Karayiannis et al. [5] gave an 85% classification accuracy over eight classes of defects (light vertical, dark vertical, light horizontal, dark horizontal, light area, dark area, wrinkle and nondefect) but the number of test samples is not mentioned.

IV. CONCLUSIONS

In this paper, a new method which incorporates the design of a wavelet frames based feature extractor with the design of an Euclidean distance based classifier has been proposed for fabric defect classification. By using MCE training method, features suitable for the classification are extracted and appropriate interactions between the feature extractor and the classifier are achieved. The evaluation results have demonstrated the efficiency of our method for fabric defect classification.

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TABLE I. THE EFFECT OF WINDOW SIZE ON THE PERFORMANCE OF DEFECT CLASSIFICATION

Window size	Classification Rate (%)
16x16	90.9
32x32	93.1
64x64	87.7

TABLE II. CLASSIFICATION PERFORMANCE IN THE MCE TRAINING

MCE Training procedure	Classification Rate (%)	
	Train	Test
Step 1	73.3	65.9
Step 2	93.6	85.0
Step 3	97.1	93.1

TABLE III. CLASSIFICATION PERFORMANCE OF EACH CLASS

Defect Class	Classification rate (%)
Broken End	100
Slack End	100
Dirty Yarn	88.8
Wrong Draw	46.8
Netting Multiples	75.0
Thin Bar	100
Mispick	100
Thick Bar	78.5
Thick Bar B	100
Nondefect	96.0
Overall	93.1

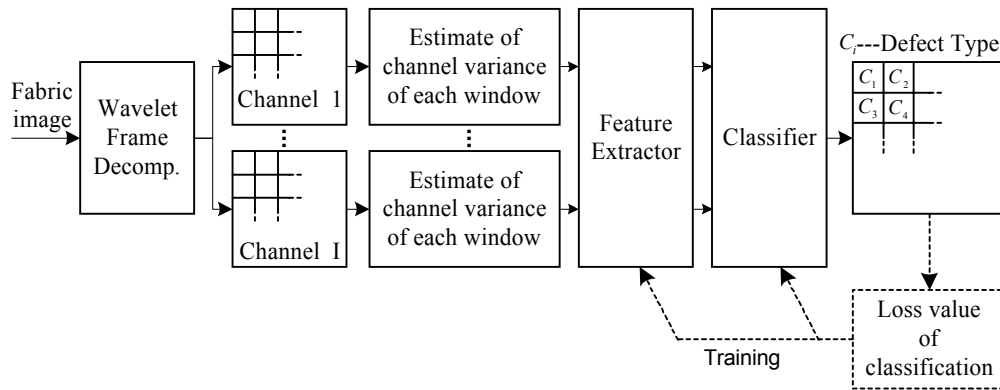


Figure 1. The proposed fabric defect classification method.

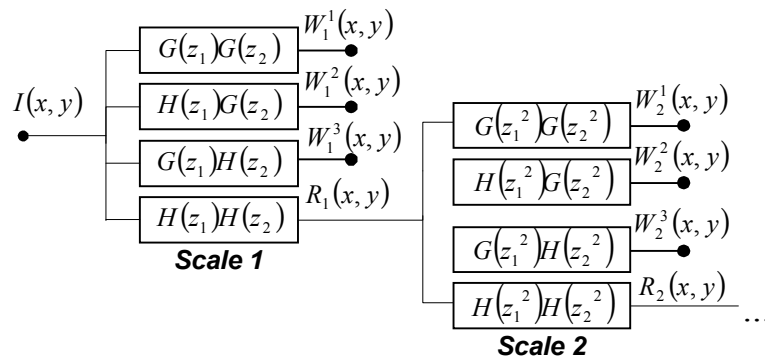


Figure 2. Filter bank implementation of 2-Dimensional wavelet frame decomposition.

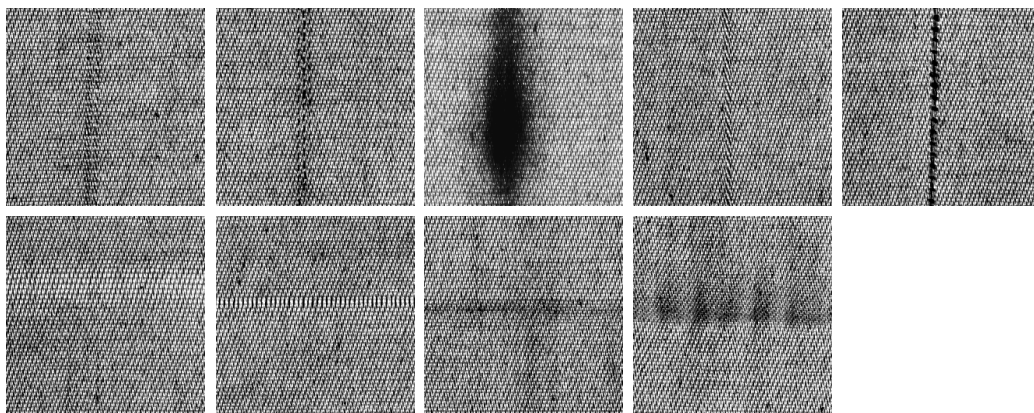


Figure 3. Fabric images containing defects: Upper row (from left to right): Broken End, Slack End, Dirty Yarn, Wrong Draw and Netting Multiples; Lower row: Thin Bar, Mispick, Thick Bar and Thick Bar Type B.

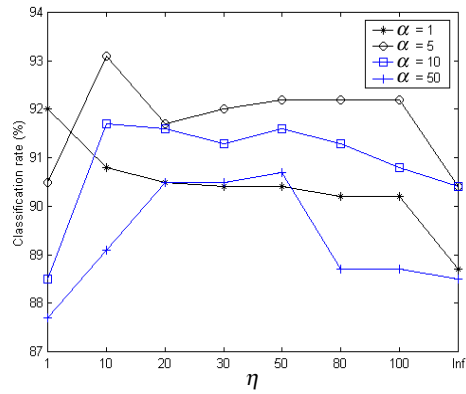


Figure 4. The effect of η and α on the performance of the defect classification using the MCE training method.

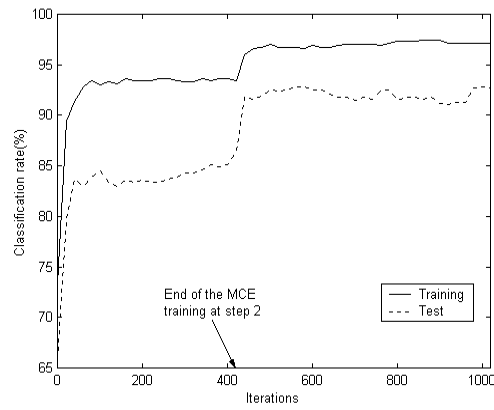


Figure 5. Learning curves of MCE training.

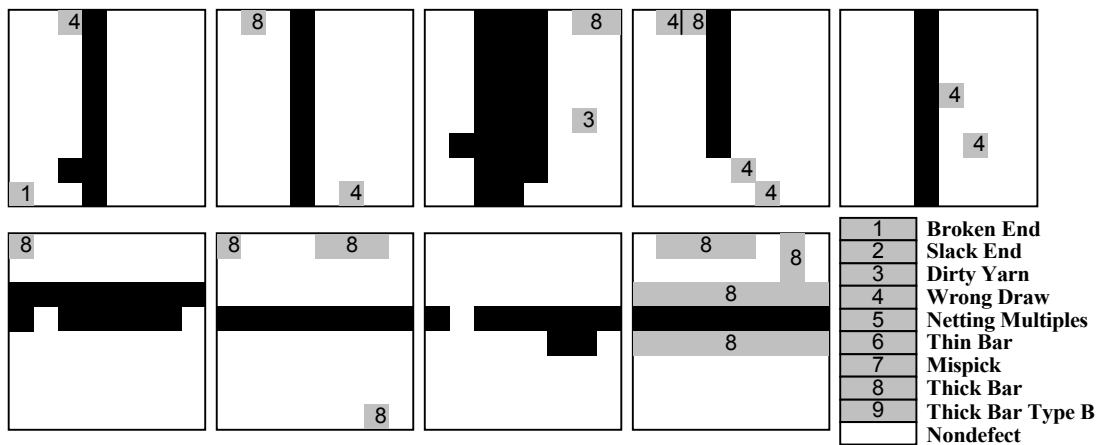


Figure 6. Classification results of the fabric images shown in Fig. (3).