involved. An assembly strategy based on three force-based compliant motions is described.

The final paper looks at a technology that will become more important in the future – micro-engineered mechanical structures, MEMS. One fundamental challenge lies in the fact that at micro-scale, micro-mechanical structures are fragile and easy to break. This paper presents the development of a polyvinylidence fluoride (PVDF) multi-direction micro-force sensing system that can potentially be used for force-reflective manipulation of micro-mechanical devices or micro-organisms over remote distances.

Fabric Defect Classification using Wavelet Frames and Minimum Classification Error-Based Neural Network

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Abstract
This paper presents a new method for fabric defect classification by using a wavelet frames feature extractor and a minimum classification error-based neural network. Channel variances at the outputs of the wavelet frame decomposition are extracted to characterize each non-overlapping window of the fabric image, which is further assigned to a defect category with a neural network classifier. In our work, a Minimum Classification Error (MCE) criterion is used in the training of the neural network for the improvement of classification performance. The developed defect classification method has been evaluated on the classification of 329 defect samples from nine types of defects and 82 non-defect samples, where an 93.4% classification accuracy was achieved.

Keywords: *Fabric inspection, defect classification, wavelet frames, neural network, minimum classification error.*

1. 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. The classification of fabric defects is an important part of FAVI. Since different types of fabric defect have different effects on the fabric product, the classification of fabric defects is necessary for the grading of fabric products. Based on defect classification, the statistics for each type of defects can be obtained, which further indicates the potential problems in certain components of the weaving machine. Moreover, on-line classification of fabric defect provides necessary information for the real-time quality control of the weaving process.

Currently, most of the FAVI systems only achieve the detection of fabric defects. However, the classification of fabric defects still remains a research topic. The large variations within each type of defect and the similarity among different types of defect are the major obstacles in fabric defect classification. Previous works on defect classification can be divided into two categories. In the first category, fabric defects are classified in terms of their shape characteristics [1,2].

The success of this approach relies on the accurate detection of the defect region. The second category is based on texture analysis. Since different type of defect locally causes distinct type of texture, the classification of defects can be formulated as a texture classification problem. To achieve that, autocorrelation function [3], gray level difference method [4] and local integration [5] have been used to extract statistical texture features for defect classification.

In this paper, a new method for defect classification is presented, which is illustrated in Fig. 1. The method has the following features:

- Wavelet frame decomposition [6] is used for feature extraction in the defect classification. Compared to the single-scale statistical texture features, channel variances at the output of the wavelet frame decomposition characterize the fabric texture at multiscale, and are able to provide more efficient discriminations among different types of defective textures.
- A neural network, which is trained by Minimum Classification Error (MCE) training method [8], is employed for defect classification. Compared to the traditional backpropagation algorithm, the MCE training method yields a network which is more consistent with the objective of minimum classification error.

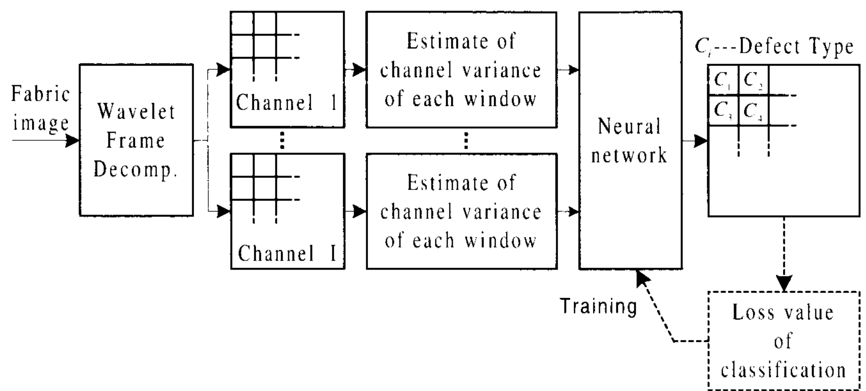

Fig. 1. The developed fabric defect classification method

The developed defect classification method has been evaluated on the classification of 329 defect samples containing nine types of defects, and 82 non-defect samples, where an 93.4% classification accuracy was achieved.

2. FABRIC DEFECT CLASSIFICATION USING WAVELET FRAMES AND MCE TRAINING

The developed defect classification method 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 non-overlapping window of the fabric image. In the classification module, a neural network classifier is used. Minimization of the classification error is achieved by using the MCE training method, which has been illustrated in Fig. 1 using dashed lines.

2.1 Feature extraction based on wavelet frame decomposition

Fig. 2 illustrates the filter bank implementation of a 2-D 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. $\{W_r^1(x,y), W_r^2(x,y), W_r^3(x,y)\}$ are the wavelet coefficients at scale r, in the diagonal, horizontal and vertical orientation respectively. $R_r(x,y)$ represents the residue signal at scale r.

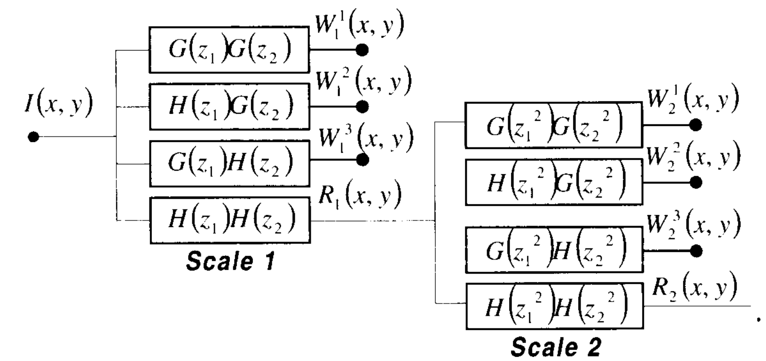

Fig. 2. Filter bank implementation of 2-D wavelet frame decomposition

Corresponding to a window in the fabric image, the channel variances are estimated as the mean energy of the wavelet coefficients in the window [6]

$$w_r^d = \underset{(x,y)\in window}{Mean}\left[W_r^d(x,y)\right]^2, \text{ for } d = 1,2,3, \tag{2.1.1}$$

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

$$\mathbf{x} = \left[w_1^1, w_1^2, w_1^3, \cdots, w_D^1, w_D^2, w_D^3\right], \tag{2.1.2}$$

where D is the depth of the wavelet frame decomposition.

The success of this approach relies on the accurate detection of the defect region. The second category is based on texture analysis. Since different type of defect locally causes distinct type of texture, the classification of defects can be formulated as a texture classification problem. To achieve that, autocorrelation function [3], gray level difference method [4] and local integration [5] have been used to extract statistical texture features for defect classification.

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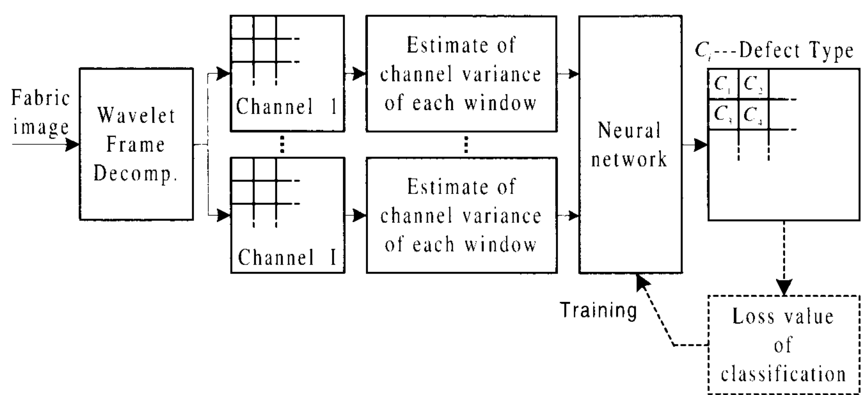

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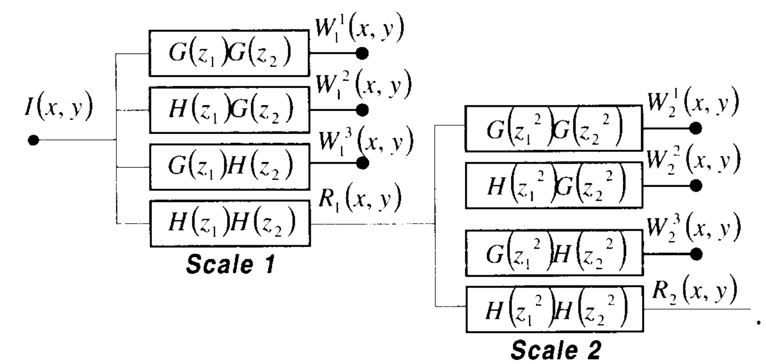

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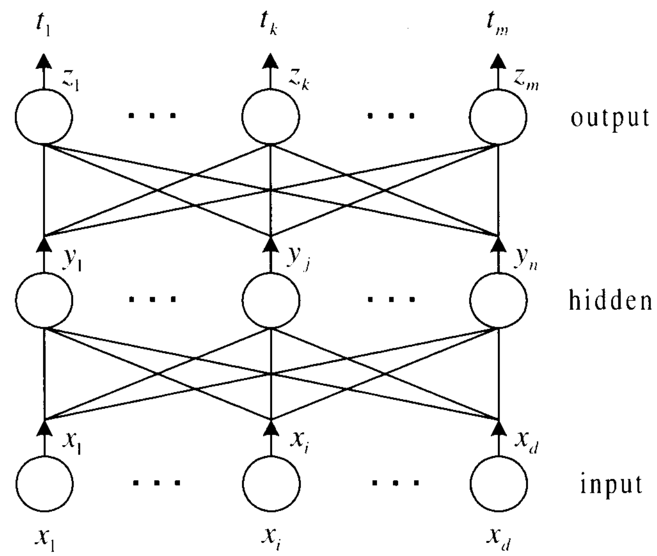


Fig. 3. A three-layer neural network

2.2 Classification using neural network

By using a neural network, the feature vector x is classified into a defect category. Fig. 3 illustrates a three-layer network. $\mathbf{x} = \{x_1, x_2, \ldots, x_d\}$ is a d-dimensional feature vector presented in the input layer. y_j is the activation output of the jth node in the hidden layer, which is obtained using the equation

$$y_j = f(nety_j) \text{ with } nety_j = \sum_{i=1}^{d} x_i v_{ij}\,, \tag{2.2.1}$$

where v_{ij} denotes the weights connecting the ith node in the input layer to the jth node in the hidden layer. $f(\cdot)$ is a nonlinear activation function, and the sigmoid function can be used. Similarly, z_k, the activation output of the kth node in the output layer, is obtained using the equation

$$z_k = f(netz_k) \text{ with } netz_k = \sum_{j=1}^{n} y_n w_{jk}\,, \tag{2.2.2}$$

where w_{jk} denotes the weights connecting the jth node in the hidden layer to the kth node in the output layer.

For the training of the neural network, the backpropagation algorithm [7] is employed. The backpropagation algorithm sets a target output $\mathbf{t} = \{t_1, t_2, \ldots, t_m\}$ for the network, where m is the number of classes. An error J_{mse} on a training pattern x is then defined as the sum-squared difference between the target output t and the actual output $\mathbf{z} = \{z_1, z_2, \ldots, z_m\}$ as follows

$$J_{mse} = \frac{1}{2}\sum_{k=1}^{m}(t_k - z_k)^2\,. \tag{2.2.3}$$

Based on the gradient descent method, the backpropagation algorithm adjusts the weights of the network to minimize the error J_{mse}

$$v_{ij}(r+1) = v_{ij}(r) - \mu\frac{\partial J_{mse}}{\partial v_{ij}}\,;\; w_{jk}(r+1) = w_{jk}(r) - \mu\frac{\partial J_{mse}}{\partial w_{jk}}\,, \tag{2.2.4}$$

where $\mu > 0$ is the learning rate, and r indexes the presentation of training patterns.

2.3 MCE training-based neural network for defect classification

A drawback of the traditional backpropagation algorithm is that the decision rule of the classifier is not directly incorporated into the error criterion J_{mse}. As a result, the weights that minimize the error J_{mse} may not be consistent with the objective of minimum classification error. One way to improve the backpropagation algorithm is the use of MCE training method proposed by Juang and Katagiri [8]. Instead of using the criterion J_{mse}, a MCE criterion J_{mce} is given below.

Given a training pattern $\mathbf{x} \in C_q$ presented to the network, where C_q denotes the qth class, a misclassification measure d is defined for $\mathbf{x}$ as follows:

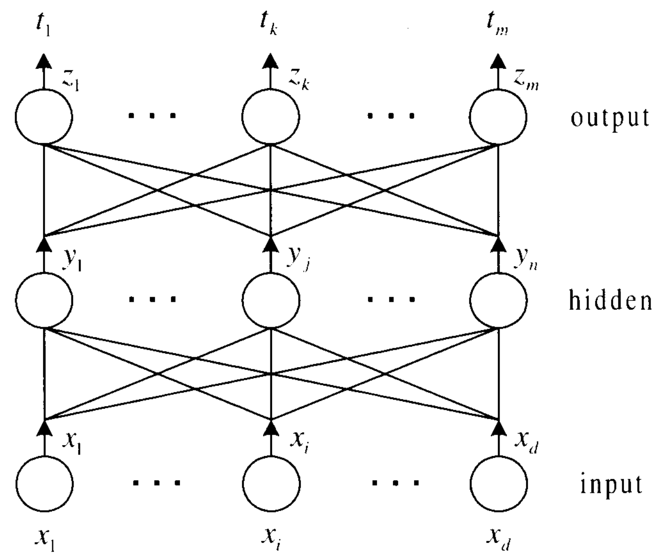
$$d = -netz_q + \ln\left[\frac{1}{m-1}\sum_{p \neq q}^{m} e^{\eta \cdot netz_p}\right]^{1/\eta}, \tag{2.3.1}$$

where η is a positive constant which controls the contribution from the competing classes. Note that, when η approaches ∞, Eqn. (2.3.1) becomes

$$d = -netz_q + \max_{p, p \neq q}\{netz_p\}, \tag{2.3.2}$$

According to the decision rule of the neural network, the misclassification measure d enumerates how likely the training pattern x is misclassified.

An error J_{mce} on the training pattern x is then defined by a smoothed zero-one function of the misclassification measure d. The sigmoid function is an example.



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$$J_{mce} = l(d) = \frac{1}{1+e^{-\alpha d}}, \text{ where } \alpha > 0. \tag{2.3.3}$$

Following the gradient descent method shown in Eqn. (2.2.4), the weights of the network are adjusted to minimize the error J_{mce}. The gradients of J_{mce} with respect to the weights v_{ij} and w_{jk} are derived as

$$\frac{\partial J_{mce}}{\partial w_{jk}} = \frac{\partial J_{mce}}{\partial d}\frac{\partial d}{\partial netz_k}\frac{\partial netz_k}{\partial w_{jk}}; \tag{2.3.4}$$

$$\frac{\partial J_{mce}}{\partial v_{ij}} = \frac{\partial J_{mce}}{\partial d}\frac{\partial d}{\partial nety_j}\frac{\partial nety_j}{\partial v_{ij}}, \tag{2.3.5}$$

where

$$\frac{\partial J_{mce}}{\partial d} = l'(d), \tag{2.3.6}$$

$$\frac{\partial d}{\partial netz_k} = \begin{cases} -1 & k = q \\ \dfrac{e^{\eta \cdot netz_k}}{\sum_{p,p\neq q}^{m} e^{\eta \cdot netz_p}} & k \neq q; \end{cases} \qquad \frac{\partial netz_k}{\partial w_{jk}} = y_j \tag{2.3.7}$$

$$\frac{\partial d}{\partial nety_j} = \left[-w_{jq} + \frac{\sum_{p,p\neq q}^{m} w_{jp} e^{\eta \cdot netz_p}}{\sum_{p,p\neq q}^{m} e^{\eta \cdot netz_p}} \right] f'(nety_j); \quad \frac{\partial nety_j}{\partial v_{ij}} = x_i. \tag{2.3.8}$$

To summarize, the MCE criterion has been used in the training of a neural network. The next section presents an evaluation of this method, and compares it with the traditional backpropagation training method.

3. EVALUATIONS

3.1 Data collection

The developed defect classification method was evaluated on the classification of nine types of typical fabric defects on plain, twill fabrics, as shown in Fig. 4. Fabric without defect should be classified into the nondefect class. In total, eighty-three fabric images containing nine types of defects were used for the evaluation. Feature vectors were extracted to characterize the non-overlapping image windows of size 32x32 pixels. Fourty-two fabric images were used for training, where 336 defect samples and 84 nondefect samples were collected. The remaining fourty-one fabric images were used for the test, where 329 defect samples and 82 nondefect samples were collected.

3.2 Evaluation results and comparison

In the feature extraction based on the wavelet frame decomposition, the Haar wavelet is used, and the feature vectors contain features from scales 1, 2 and 3. The classification rate using the developed method are summarized in Table 1. The method achieves 93.4% accuracy in the classification of the test samples. For a comparative study, the neural network trained by the traditional backpropagation algorithm was also implemented, and its classification rate is 91.4%. Hence, the neural network trained by the MCE method is more consistent with the objective of the minimum classification error.

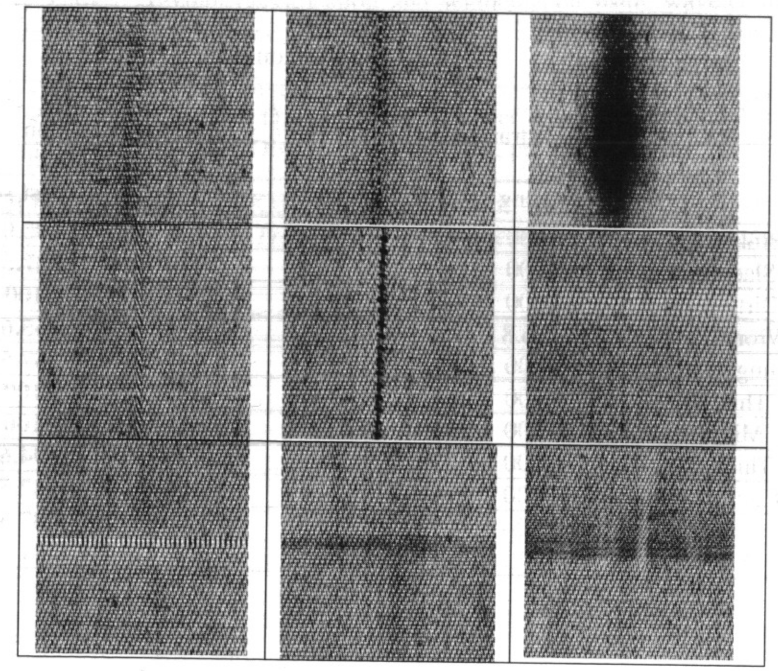

Fig. 4. Fabric images containing defects: Upper row (from left to right): BrokenEnd, SlackEnd, Dirty Yarn; Middle row: Wrong Draw, Netting Multiples, ThinBar; Lower row: Mispick, Thick Bar, Thick Bar type B

Comparing with results by other researchers, Brzakovic and Vujovic [1] gave a classification accuracy of 85% for 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 and Abu-Rezeq [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.* [4] gave an 85% classification accuracy over eight classes of defects (light vertical, dark vertical, light horizontal, dark horizontal, light area, dark area, wrinkle and non defect) but the number of test samples is not mentioned.

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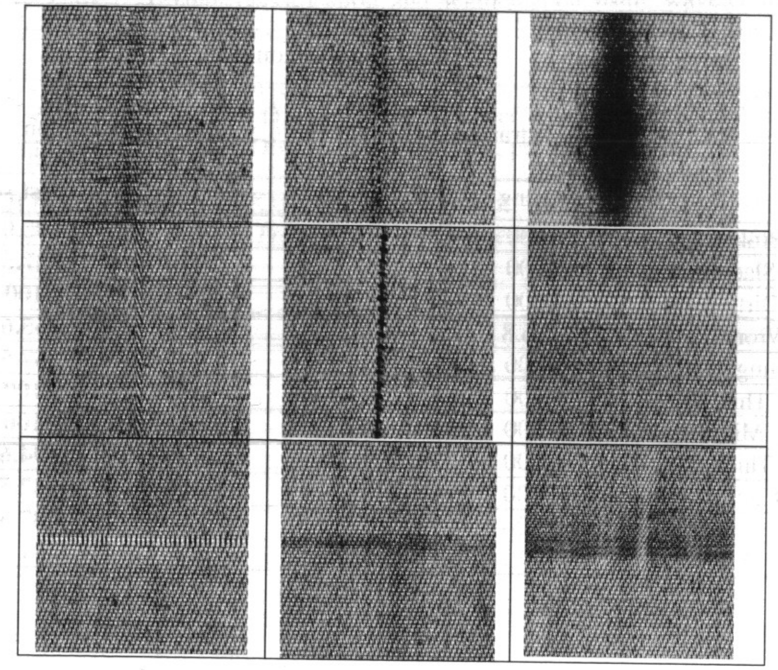

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Table 1. Classification rate of the developed defect classification method

Defect Type	Classification rate (%)			
	MCE training method		Traditional backpropagation training method	
	Training set	**Test set**	Training set	**Test set**
Broken End	100	**90.0**	100	**95.0**
Slack End	100	**97.5**	100	**97.5**
Dirty Yarn	100	**100**	100	**100**
Wrong Draw	96.8	**75.0**	96.8	**65.6**
Netting Multiples	100	**100**	100	**87.5**
Thin Bar	100	**100**	100	**100**
Mispick	100	**100**	100	**100**
Thick Bar	100	**92.8**	100	**94.6**
Thick Bar B	100	**100**	100	**82.5**
Nondefect	100	**87.8**	100	**87.8**
Overall	99.7	**93.4**	99.7	**91.4**

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Thick Bar	100	**92.8**	100	**94.6**
Thick Bar B	100	**100**	100	**82.5**
Nondefect	100	**87.8**	100	**87.8**
Overall	99.7	**93.4**	99.7	**91.4**

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