Fabric defect detection system based on digital image processing

Zhaozhun Zhong[1]*, Pengjie Qi[2], Miao Guan[1], Yuedong Xia[2], Yuanhui Fu[3]

[1]*School of Iron and Steel Soochow University, Suzhou City, Jiangsu Province, PR China, 215021*

[2]*School of Mechanical and Electrical Engineering Soochow University, Suzhou City, Jiangsu Province, PR China, 215021*

[3]*Humanetics Innovative Solutions, Inc., Plymouth, USA, 48170*

Received 30 October 2014, www.cmnt.lv

Abstract

A fabric defect detection system based on digital image processing for textile fabric is proposed in this paper. The approach for the classification and identification of three commonly encountered classes of fabric defects (holes sto, missing end and mispick) is studied. The developments of both the hardware and software structures are presented. Firstly, median filter preprocessing and image segmentation based on Otsu threshold are applied to localize the fabric defects. Secondly, the features based on grey-level histogram and geometry are extracted. Thirdly, the classification and identification are accomplished by the method of artificial neural network based on the extracted features. Finally, a variety of textile images with different defects are tested to evaluate the performance of the proposed defect detection system. The experiment results indicate that the proposed system works efficiently with high accuracy, which can meet the requirements of the textile industry.

Keywords: fabric defect detection system, digital image processing, image segmentation, defects classification

1 Introduction

The textile industry plays an important role in the national economy. The throughput of a modern textile process is quite impressive, expensive mechanical equipment and modern control strategies are necessary in the process. The major specifications of the product that should be satisfied are quality and stable operation of the process. As for quality control, the fabric defect detection is a major concern because fabric defects may reduce the price of a product by 45% to 65%. The traditional fabric defect detection is generally manipulated by manual inspection, which suffers from the problems associate with human fatigue and boredom, inconsistency and high inspection cost. In general, only about 60%~70% of fabric defects can be detected by the most skilled inspectors under the conditions that the width of the fabric is less than 2m and the speed is less than 30m/min [1]. In order to overcome the shortages of human inspection, automated visual inspection system could be a possible way to detect possible defects in fabric which provides a more reliable and consistent quality control process [2, 3].

Automated fabric defect detection system works based on the fact that textile faults normally have features which are different from the features of the original fabric. As one of the most intriguing problems in visual inspection, fabric defect detection has attracted great attention in recent years. The detection of fabric defects can be considered as a segmentation and identification problem. A variety of algorithms have been proposed to solve the problem. For a plain fabric, Zheng et al. [4] reported that 92% of the defects could be detected simply by distance calculation among images. For complicated fabrics such as denim and twill fabrics, some effective schemes have also been proposed [5, 6]. The proposed algorithms can be categorized into five major classes: spectral, statistical, geometrical, structural and model based. Among all the five major classes, the spectral approach, which is based on the periodicity of the texture feature, is regarded as the most effective one for woven fabrics in literature. For spectral approach commonly used techniques are wavelet transform [7, 8], Fourier transform [9, 10], Gabor analysis [11, 12] and so on. As for real time fabric defect detection, Mak and Peng [13] proposed a new scheme and apparatus using odd and even symmetric real-valued Gabor filters, which are designed based on the optimally extracted texture features from a non-defective fabric image using Gabor wavelet network. A real time fabric defect detection system based on an embedded DSP (Digital Signal Processor) platform is proposed by Raheja [14, 15], in which textural features of fabric images are extracted based on grey level co-occurrence matrix and a sliding window technique is used for defect detection. A neural network approach is proposed for defect classification and identification on leather fabric in [16, 17].

Along the line of this research trend, an automatic fabric defect detection system based on machine vision is proposed in this paper. The fundamental hardware and

***Corresponding author** e-mail: nustzzz@163.com

software structures of the proposed system are introduced. Median filter is selected for image pre-processing and Ostu threshold is chosen as the image segmentation method according to the comparison studies. Seven features extracted from the grey-level histogram and six extracted geometric features are used for fabric defect classification and identification. The classification and identification are accomplished by a multi-layered neural network which is appropriate for pattern classification. The proposed neural network is trained by fabric defect samples and tested by on-line detected defects. The experiment results verify the effectiveness of the proposed method.

The rest of the paper is organized as follows: The architecture of the fabric defect detection system is introduced in Section 2, image pre-processing and segmentation of fabric defects are discussed in Section 3. Feature extraction and defect classification as well as the experiment results are given in Sections 4 and 5 respectively. Finally, the paper is concluded in section 6.

2 Architecture of the fabric defect detection system

2.1 SYSTEM DESIGN

As illustrated in Figure 1, the fabric defect detection system consists of an image acquisition module, a defect detection module, a feature extraction module and a defect classification module. The system can be divided into three parts: the first part acquires the fabric image, the second part pre-processes the obtained images and detects the images with defects, the third part accomplishes the task of segmentation and localization of the defect area for feature extraction, and finally classifies the detected defects.

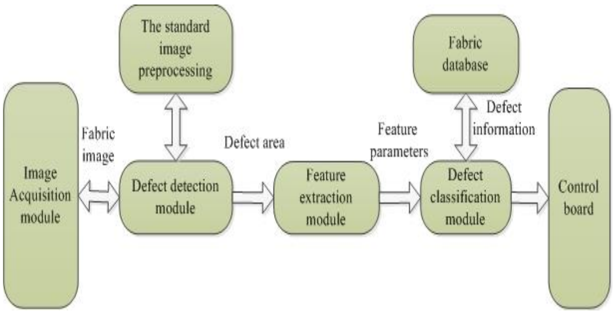


FIGURE 1 Architecture of the fabric defect detection system

2.2 HARDWARE STRUCTURE

The hardware part of the fabric defect detection system is mainly composed of image acquisition system and computer control system. Image acquisition system contains lighting equipment (LED light source), CCD array cameras, image capture card and so on. The hardware structure diagram of the system is shown in Figure 2. The roller system and guide rail of the inspection system are designed to ensure the smooth and even movement of the fabric. The effects of mechanical vibration and wrinkles can be reduced by adjusting the working tension. LED light source is equipped as back lighting source which provides illumination to minimize the effects of shadows and glare. CCD array cameras are installed on the inspection bridge, which provides three degrees-of-freedom movement for the camera to guarantee the quality of captured images. The acquired images are sent to the parallel computers by an interface called camera link, which is of high data transfer rate. The synchronization of the fabric and camera is ensured by the means of a disc encoder.

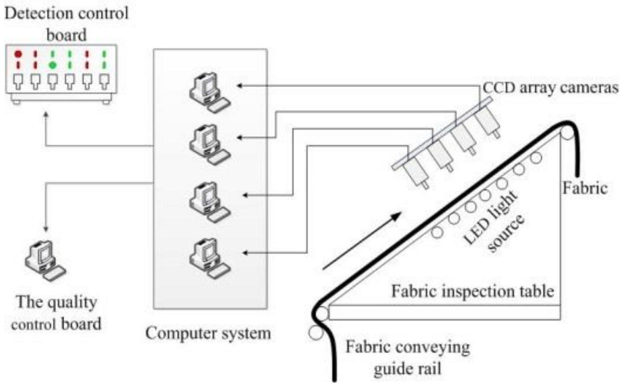


FIGURE 2 The hardware structure of the system

2.3 SOFTWARE STRUCTURE

An effective defect detection schema is regarded as the core part of the automated inspection system. In general, it can be divided into four steps: image pre-processing, image segmentation and localization, feature extraction, defect classification and identification. The specific methods will be introduced later in the following paragraphs. Figure 3 gives the basic procedure of the image processing schema.

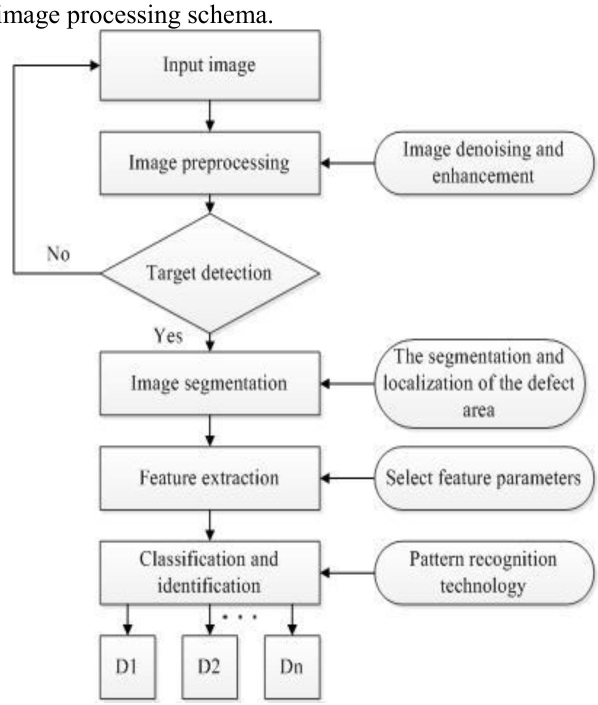
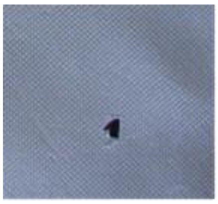


FIGURE 3 The basic procedure of the image processing schema

3 Image pre-processing and segmentation

Due to the technology and equipment faults in the process, a variety of defects are frequently encountered in fabrics, in terms of texture pattern violation, yarn misplacements, weaving defects and so on. The defects can be categorized into different types according to different classification methods. For example, they can be divided into point defect, line defect and planar defect according to the geometrical characteristics of the defects; according to the texture feature of defects, there will have statistical distortion defect, direction distortion defect and unstructured distortion defect. It is difficult to identify all the variety of defects encountered in the textile industry even by the most advanced automated visual inspection system. This paper limits the variety of fabric defects into three kinds of the most frequently encountered ones, that is, holes sto, missing end and mispick. For the sake of clarity, the images of these defects along with the normal fabric are given in Figure 4.


4a) Normal fabric


4b) Holes sto


4c) Missing end

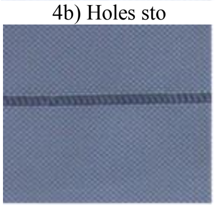

4d) Mispick

FIGURE 4a-Normal fabric, 4b, 4c, 4d-Defect fabrics

3.1 DEFECT IMAGE PRE-PROCESSING

During the process of image acquisition, the fabric image will get different degrees of noises due to the influence of environmental factors and the system itself. The noises will have a significant impact on the subsequent processing of the image. In order to reduce the effects of the noises, the acquired images should be pre-processed before further processing. During the process of image pre-processing, image denoising is the most crucial step because it directly affects the final effect of image processing. In the literature, mean filter and median filter are the most commonly used spatial filter methods.

Mean filter is an intuitive way of filter, it can effectively suppress noises to smooth the image, but it also has a negative impact of making the image edge blur. Median filter is a commonly used nonlinear spatial filter. It is particularly effective in the presence of impulse noises and it can effectively overcome the blur effect of the details brought by the linear filter. But median filter is not quite qualified for disposing the image with lots of details. According to the comparison experiments between the two filters, the median filter is more suitable for the characteristics of the fabric image and is chosen as the filter for image pre-processing.

3.2 FABRIC DEFECT IMAGE SEGMENTATION

After pre-processing, the first step should be the judgement of whether there are suspected defects in the image area, which is known the target detection. The algorithms of target detection should be as simple as possible, because all collected images should be processed in a given short time interval. Complex algorithms will increase the amount of calculation and reduce the speed of processing. Most of the images captured by cameras are normal (without defects) which do not need further processing. For the images with defects, segmentations are needed to separate the defective area from the background for further processing. Image segmentation is a key part of fabric defect detection technique, the effect of segmentation directly affects the image feature extraction and identification of defects. Generally speaking, image segmentation methods can be divided into four categories: threshold-based segmentation, edge-based segmentation, region-based segmentation and specific theory-based segmentation. According to the characteristics of the selected fabric, edge-based segmentation and Otsu threshold-based segmentation are chosen for the comparison experiments.

z_1	z_2	z_3
z_4	z_5	z_6
z_7	z_8	z_9

-1	-2	-1
0	0	0
1	2	1

-1	0	1
-2	0	2
-1	0	-1

FIGURE 5 Sobel operator templates (Z is the grey value)

1) Edge-based segmentation: Sobel operator and Roberts operator Sobel operator and Roberts operator are the commonly used edge detection operators, in Figure 5, z_5 is defined as the centre point $f(x,y)$, z_1 is $f(x-1,y-1)$, and so on.

The Sobel operator uses 3×3 templates for gradient calculation and increases the weights of the four neighbouring pixels of the centre pixel. The Sobel operator can be formulated as:

$$g_x=\frac{\partial f}{\partial x}=(z_7+2z_8+z_9)-(z_1+2z_2+z_3) \quad (1)$$

$$g_y=\frac{\partial f}{\partial y}=(z_3+2z_6+z_9)-(z_1+2z_4+z_7) \quad (2)$$

$$|g(x,y)|=\sqrt{(g_x{}^2+g_y{}^2)}\approx|g_x|+|g_y| \quad (3)$$

The Roberts operator uses 2×2 templates and the effect is not so good due to the lack of explicit central point. The templates of Roberts operator are given in Figure 6.

-1	0
0	-1

a)

0	-1
-1	0

b)

FIGURE 6 Roberts operator templates

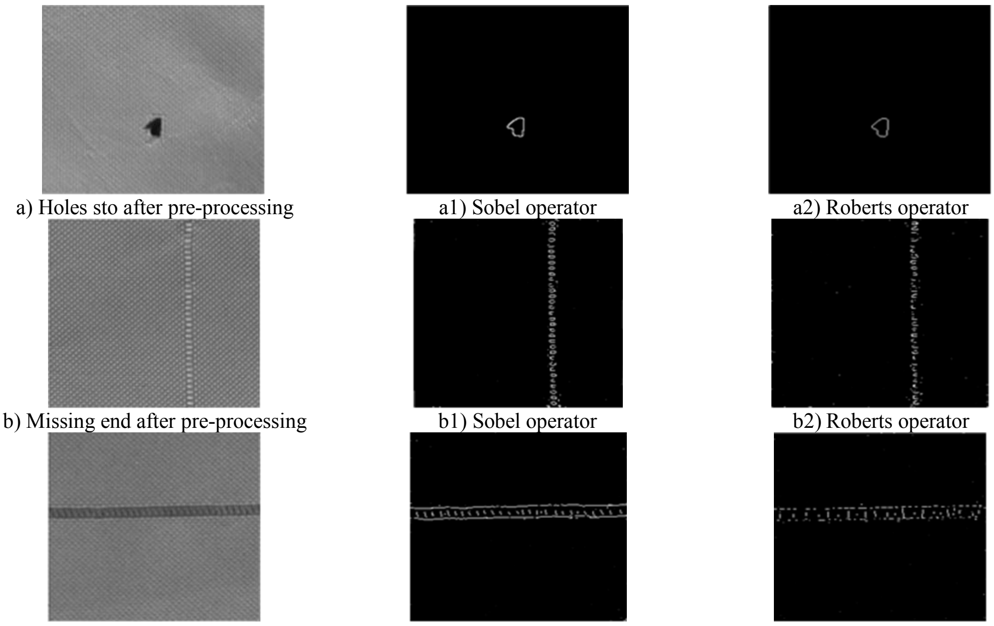
The Roberts operator can be formulated as:

$$g_x = \frac{\partial f}{\partial x} = (z_9 - z_5) \tag{4}$$

$$g_y = \frac{\partial f}{\partial y} = (z_8 - z_6) \tag{5}$$

$$|g(x,y)| = [(z_9 - z_5)^2 + (z_8 - z_6)^2]^{\frac{1}{2}} \tag{6}$$

The three typical kinds of fabric defect images (holes sto, missing end and mispick) are processed using the edge-based segmentation (Sobel operator and Roberts operator). The results are given in Figure 7.



a) Holes sto after pre-processing a1) Sobel operator a2) Roberts operator
b) Missing end after pre-processing b1) Sobel operator b2) Roberts operator
c) Misspick after pre-processing c1) Sobel operator c2) Roberts operator

FIGURE 7 Edge detection segmentation image of defects

The experimental results show that the Sobel operator works better in the treatment of the two kinds of defects (missing end and mispick). Their edge is much clearer and the closure is better. The Sobel operator has the smooth effect on image noises and is less affected by noises. The bigger the template is, the better the effect of edge extraction is. But the boundary extracted by Sobel operator is not so good, which makes the target region not obvious.

2) Image segmentation based on Ostu threshold: Threshold segmentation is the method that divides the image pixels into several parts by setting one or more threshold to achieve the aim of image segmentation. This paper uses single threshold segmentation, which only selects a threshold T to divide the image into two parts (target and background) by comparing the grey value of pixels with the threshold *T*. The segmentation based on threshold is the commonly used method thanks to its simplicity and calculation speed. Otsu threshold segmentation determines the threshold by calculating the between-class variance. The basic idea is as follows: suppose the pixel number of the image is *N*, the grey-level range is [0, *L*-1], the number of pixels for each grey-level is N_i, probability is $P(i)$. Using the threshold *T* to divide the pixels of the image into two classes C_1 and, the grey-level range of C_1 is [0, *T*] and C_2 is [*T*+1, *L*-1], that is, C_1 consists of all the pixels in the image with intensity values in the range [0,T] and C_2 consists of the pixels with intensity values in the range [*T*+1, *L*-1].

As a result the average intensity value of the entire image is given by

$$u_T = \sum_{i=0}^{L-1} iP(i) \tag{7}$$

the mean intensity value of C_1 is

$$u_1 = \frac{\sum_{i=0}^{T} iP(i)}{\sum_{i=0}^{T} P(i)} = \frac{\sum_{i=0}^{T} iP(i)}{\omega_1} \tag{8}$$

and the mean intensity value of C_2 is

$$u_2 = \frac{\sum_{i=T+1}^{L-1} iP(i)}{1 - \sum_{i=0}^{T} P(i)} = \frac{\sum_{i=T+1}^{L-1} iP(i)}{1-\omega_1} = \frac{\sum_{i=T+1}^{L-1} iP(i)}{\omega_2} \tag{9}$$

according to the above formulas and

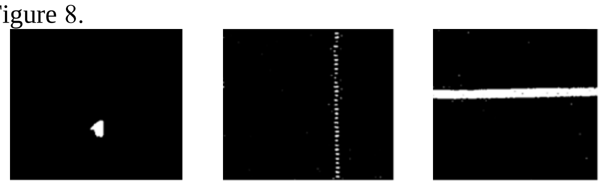
$$u_T = \omega_1 u_1 + \omega_2 u_2 \quad (10)$$

the between-class variance is given as:

$$\sigma_B^2 = \omega_1 \left(u_1 - u_T\right)^2 + \omega_2 \left(u_2 - u_T\right)^2 . \quad (11)$$

The threshold T is usually set as the one which maximizes the between-class variance σ_B^2.

Three typical kinds of fabric defect images (holes sto, missing end and mispick) are processed utilizing the Otsu threshold with the best thresholds (0.4, 0.56 and 0.42, respectively). The images after processing are shown in Figure 8.



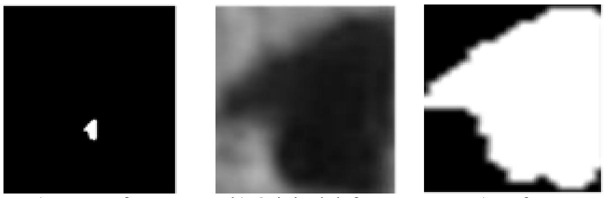
a) Holes sto b) Missing end c) Mispick

FIGURE 8 Threshold segmentation image of defects

The experimental results show that the Otsu threshold segmentation method can effectively segment the defect image to separate the target and background. Compared with the Sobel operator, the target segmented by the threshold is much more obvious, which facilitates the subsequent feature extraction process. Therefore, the threshold segmentation method is adopted in this paper.

3.3 FABRIC DEFECT LOCALIZATION

The fabric defect region still needs further processing before feature extraction. On one hand, the image after segmentation still has a certain amount of noises which needs further processing. On the other hand, the segmentation region needs to be localized, which is to find out the smallest rectangle that can completely contain the defect area. For each pixel, collecting the numbers n_0 and n_1 of its 0 and 1 valued neighbours, if the maximum number of n_0 and n_1 is less than a given threshold, the pixel point is regarded as noise and is removed. Then finding out the minimum and maximum values of the abscissa and ordinate of the 1 valued pixels, which determine a rectangle. The determined rectangle is the required localization area. For example, the holes sto images after segmentation and localization are illuminated in Figure 9.



a) Image after segmentation b) Original defect image c) Defect localization image

FIGURE 9 Holes sto localization image

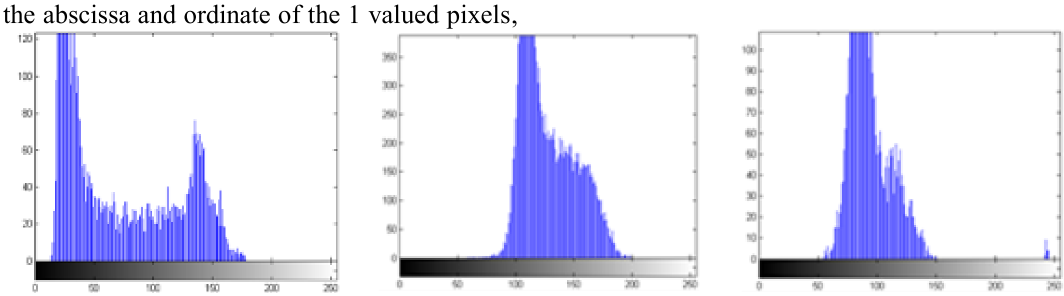
4 Feature extraction

1) Feature extraction based on grey-level histogram: the grey-level histogram is about the statistical distribution of image grey value. Feature extraction method based on grey-level histogram is easy to achieve, but suffers from the disadvantages associated with large amount of calculation and low resolution. Seven feature parameters including grey average $\bar{i}$, variance σ^2, energy H_p, entropy H_e, the maximum grey value G_m, the minimum grey value G_n and the maximum difference of grey value G are extracted from grey-level histogram in this paper.

For the sake of clarity, the typical grey-level histogram images of localized holes sto, missing end and mispick are shown in Figure 10. And the feature parameters extracted from the histograms are given in Table 1.

TABLE 1 Histogram feature extraction

Feature parameters	Holes sto	Missing end	Mispick
Average	70.1956	127.3415	93.6002
Variance	48.0994	23.0919	19.1240
Energy	2.075e-3	5.067e-5	2.133e-4
Entropy	6.8279	4.3393	10.9437
Maximum grey value	178	199	245
Minimum grey value	14	59	54
Maximum difference of grey value	164	140	199



a) Holes sto histogram b) Missing end histogram c) Mispick histogram

FIGURE 10 Histogram of detects

2) Feature extraction based on geometry: geometric characteristic is the basic feature of the defect area, which includes it's shape information. For geometric feature extraction, the first step is the binarization of the defect image. Then six feature parameters are selected:

- length L, which represents the horizon length of the defect area and is calculated through the horizontal projection,
- width W, which represents the vertical width of the defect area and is calculated through the vertical projection,
- the ratio of length and width B, which general describes the degree of warp or weft of the defect,
- area S, the area of the defect S is the sum of all pixels whose grey value is 1 in the binary image,
- perimeter C, which is the sum of all the pixels in the region R of the segmentation edge,
- dispersion A, it is a measure of the defect shape. For graphics with the same area, the smaller the perimeter is, the compacter the image is.

Geometric features extracted from typical defect images (localized holes sto, missing end and mispick) are shown in Table 2.

TABLE 2 Geometry feature extraction

Feature parameters	Holes sto	Missing end	Mispick
Length L	21	13	256
Width W	28	252	29
Ratio of length and width B	0.75	0.0515	12.8
Area S	353	536	3487
Perimeter C	94	415	784
Dispersion A	25.031	321.31	176.271

5 The fabric defect classification and identification

Classification and identification is the last step of fabric defect detection, which is also the objective of the defect detection system. The final classification and identification are based on the extracted features of the fabric defects. The classification methods can be summarized into three categories: statistical, syntactic and fuzzy logic [18]. Classification based on BP (Back Propagation) neural network is one of the most important statistical methods and is also the most commonly used one.

5.1 BP NEURAL NETWORK: A BRIEF REVIEW

Artificial neural networks, which are inspired by the animal's central nervous systems, are presented as systems of interconnected neurons and used to approximate unknown functions. Due to the adaptive nature of neural networks, they are capable of machine learning and pattern recognition. There are mainly two connection forms of artificial neural networks: hierarchical and all connection. Hierarchical neural network is made up of several layers, the number of neurons in each layer can be selected according to the requirements of the problem. Error back propagation neural network is one of the typical hierarchical neural networks, which is widely used in classification, function approximation and so on.

In general, BP neural network uses the feed-forward network structure, which consists of three kinds of layers: input layer, hidden layers (middle layers) and output layer. The design of BP neural network is to determine the number of layers, the number of neurons in each layer and various parameters. The structure is illustrated in Figure 11.

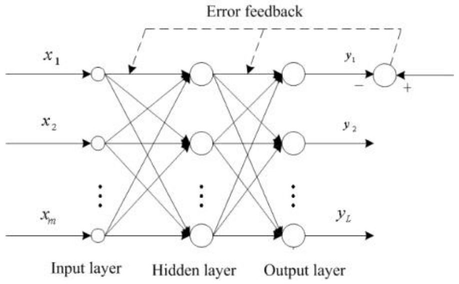


FIGURE 11 The BP neural network structure

The working process of the BP neural network can be divided into two stages. The first stage is the training of the neural network model by known samples, which essentially means selecting one model from the set of allowed models to minimize the cost criterion. Most of the algorithms used in training artificial BP neural network adjust the connection weights in the network in each step to minimize the mean square error between the desired target value and the actual output value of the network. The adjustments of the connection weights are generally based on the gradient descent method. The second stage is the application of the neural network for the classification and identification of fabric defects. The specific working process is shown in Figure 12.

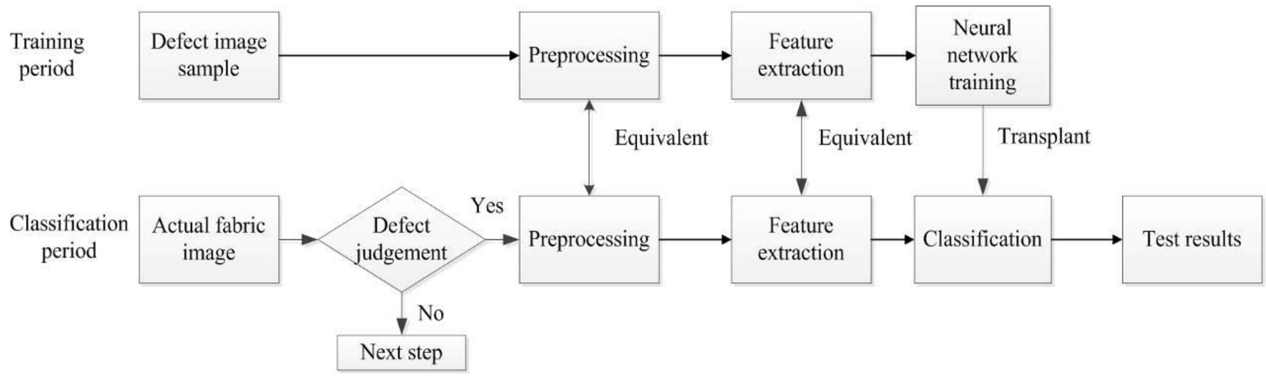


FIGURE 12 The working process of the BP neural network

5.2 THE DESIGN AND ANALYSIS OF THE FABRIC DEFECT CLASSIFIER

The multi-layered perceptron, which is regarded as the most appropriate neural network for pattern classification, is adopted for the fabric defect classifier. According to the characteristic of the fabric defects and the comparison study of network structures, a three-layered network (input layer, output layer and a hidden layer) is selected. The number of neurons in the input layer is set as the number of the input features 13. Since three typical classes of fabric defects (holes sto, missing end and mispick) are investigated, the number of neurons in the output layer is set as the number of the defined defect classes 3. As for the hidden layer, the number of the neurons is determined by experimentation which results in 8.

The three-layered network is then trained by supervised learning with defect samples which have been classified into three classes by human review in advance. All the initial weights are set to small random values at the beginning. All the input features are normalized to [0,1]. The learning rate is set as 0.3. Totally 100 defect samples are used for training and the convergence trajectory of the mean square error of the neural network is given in Figure 13.

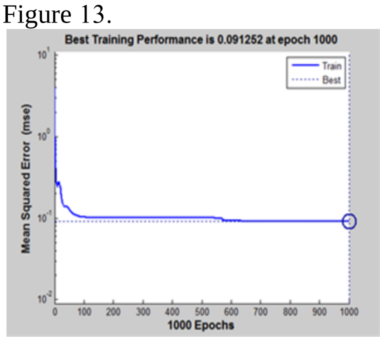


FIGURE 13 The convergence trajectory of the mean square error

After the training of the BP neural network, classification will be performed and each defect will be assigned to one of the specific defect classes. The process of the classifier for defects classification is shown in Figure 14.

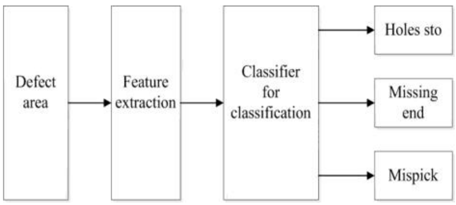


FIGURE 14 The classification and identification process of fabric defects

Totally 60 defect images are detected and used for the classification test: 20 defect samples for each of the three defect classes (holes sto, missing end and mispick). The classification result of the proposed classifier is given in Table 3.

TABLE 3 The classification result

Defect types	Test samples	Indentified	Accuracy
Holes sto	20	20	100%
Missing end	20	18	90%
Mispick	20	19	95%

The experimental results show that the identification rate of the classifier for holes sto is 100%, and the identification rates for missing end and mispick are both over 90%, which verify the effectiveness of the proposed classifier.

6 Conclusions

The development of an automated vision system to identify and classify defects on fabrics is presented in this paper. The hardware and software structures of the system are introduced. The defect detection process consists of image acquisition, image pre-processing, segmentation, localization and finally classification. A three-layered neural network is proposed for the classifier which results in high classification accuracy. Experiment results verify the effectiveness of the proposed method.

Future research work could be the issues associating with the industrial application, such as on-line computation burden, inspection cost, optimization of the algorithms and so on.

Acknowledgments

This work was partially supported by National Natural Science Foundation of China (61304095 & 61403254), Natural Science Foundation of Jiangsu Province (BK20130317), Shanghai Natural Science Foundation of China (13ZR1428500), Jiangsu Planned Projects for Postdoctoral Research Funds (1302103B) and Suzhou Science and Technology Program (SGZ2013135).

References

[1] Karayiannis Y A, Stojanovic R, Mitropoulos P, et al. 1999 Defect detection and classification on web textile fabric using multiresolution decomposition and neural networks *Proceedings of 6th IEEE International Conference on Electronics Circuits and Systems(Cat. No.99EX357)* **2** 765-8

[2] Mahajan PM, Kolhe SR, Patil PM 2009 A review of automatic fabric defect detection techniques *Advances in Computational Research* **1**(2) 18-29

[3] Stojanovic R, Mitropulis P, Koulamas C, et al. 2000 An approach for automated defect detection and neural classification of web textile fabric *Machine Graphics and Vision* **9**(3) 587-607

[4] Zheng G, Wang J 2007 Fabric defect detection method based on image distance difference *2007 8th International Conference on Electronic Measurement and Instruments ICEMI* 2822-5

[5] Kumar A, Pang G 2000 Fabric defect segmentation using multichannel blob defectors *Optical Engineering* **39**(12) 3176-90

[6] Kumar A, Pang G 2001 Identification of surface defects in textured materials using wavelet packets *Conference Record - IAS Annual Meeting (IEEE Industry Applications Society)* **1** 247-51

[7] Sari-Sarraf H, Goddard J S 1999 *IEEE Transactions on Industry Applications* **35**(6) 1252-9

[8] Hu M C, Tsai I S 2000 Fabric inspection based on best wavelet packet bases *Textile Research Journal* **70**(8) 662-70

[9] Chan CH, Pang G 2000 *IEEE Transactions on Industry Applications* **36**(12) 1267-76

[10] Tsai D M, Heish C Y 1999 Automated surface inspection for directional textures *Image and Vision Computing* **18**(1) 49-62

[11] Bodnarova A, Bennamoun M, Latham S 2002 Optimal Gabor filters for textile flaw detection *Pattern Recognition* **35**(12) 2973-91

[12] Kumar A, Pang G 2002 *IEEE Transactions on Industry Applications* **38**(2) 425-40

[13] Mak K L, Peng P 2008 An automated inspection system for textile fabrics based on Gabor filters *Robotics and Computer-Integrated Manufacturing* **24**(3) 359-69

[14] Stepien K 2014 Research on a surface texture analysis by digital signal processing methods *Tehnicki Vjesnik-Technical Gazette* **21**(4) 689-95

[15] Raheja J L, Ajay B, Chaudhary A 2013 Real time fabric defect detection system on an embedded DSP platform *Optik* **124**(21) 5280-4

[16] Kwak C, Ventura J A, Tofang-sazi K 2000 A neural network approach for defect identification and classification on leather fabric *Journal of Intelligent Manufacturing* **11**(5) 485-99

[17] Zhang J-H, Liu Y-Q, Tian D 2013 The short-term wind power forecast based on phase-space reconstruction and neural networks *Journal of Digital Information Management* **11**(1)40-5

[18] Zhou Q Q, Zhou Q F, Ning Y P, Yang F, Lei J Y, Tian R, Liu M D 2012 A comparison of pattern classification approaches for structural damage identification *Journal of Digital Information Management* **10**(2) 126-30

Authors

Zhaozhun Zhong, born in September, 1980, Suzhou City, Jiangsu Province, China

Current position, grades: the lecturer of School of Iron and Steel, Soochow University, China.
University studies: PhD in Automation from Shanghai Jiaotong University in China.
Scientific interests: digital image processing, real-time control and simulation.
Publications: 15 papers.
Experience: teaching experience of 3 years, completed 3 scientific research projects.

Pengjie Qi, born in May, 1989, Suzhou City, Jiangsu Province, China

Current position, grades: the graduate student of School of Mechanical and Electrical Engineering, Soochow University, China.
University studies: B.Sc. in Mechanical Engineering from Jiujiang University of Jiangxi in China.
Scientific interest: digital image processing, pattern recognition.
Publications: 3 papers.
Experience: completed 1 scientific research projects.

Miao Guan, born in February, 1979, Suzhou City, Jiangsu Province, China

Current position, grades: the researcher of School of Iron and Steel, Soochow University, China.
University studies: M.Sc. in Computer Science from Soochow University in China.
Scientific interest: digital image processing.
Publications: 10 papers.
Experience: completed 2 scientific research projects.

Yuedong Xia, born in November, 1992, Suzhou City, Jiangsu Province, China

Current position, grades: the graduate student of School of Mechanical and Electrical Engineering, Soochow University, China.
University studies: B.Sc. in Automation from Soochow University in China.
Scientific interest: real-time control.
Publications: 3 papers.
Experience: completed 1 scientific research projects.

Yanhui Fu, born in October, 1978, Plymouth, USA

Current position, grades: senior project engineer of Humanetics Innovative Solutions, Inc., Plymouth, USA.
University studies: M.Sc. in Mechanical Engineering from Nanjing University of Science and Technology in China.
Scientific interest: mechanical system design.
Publications: 5 papers.
Experience: completed 2 scientific research projects.