Asian Journal of Information Technology 13 (6): 308-312, 2014
ISSN: 1682-3915

An Intelligent System for Automatic Fabric Inspection

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Abstract: Quality inspection is one of the major problem for fabric manufacturers in textile industries. Textile manufacturing is a process of converting various types of fibers into yarn, woven then into fabric. Weaving is a process of interlacing two distinct yarns namely warp and weft. A fabric fault is any abnormality in the fabric that hinders its acceptability by the user. At present, the fault detection is done manually after production of a sufficient amount of fabric. The nature of work is very dull and repetitive. There is a possibility of human errors with high inspection time in manual inspection, hence it is uneconomical. This study proposed a computer based inspection system for identification of defects in the woven fabrics using image processing and Artificial Neural Network (ANN) with benefits of low cost and high detection rate. The defects consist of hole, stain, warp float and weft float. The inspection system first acquires high quality vibration free images of the fabric. Then, the acquired images are first normalized and preprocessed using image processing techniques then the preprocessed image is converted into binary images based on the threshold value. From the binary image features are extracted and these extracted features are given as input to the Artificial Neural Network (ANN) which uses Back Propagation algorithm to calculate the weighted factors and generates the output. The ANN is trained by using 115 defect free and defected images.

Key words: Artificial Neural Network (ANN), fault detection, image processing, Back Propagation algorithm, feature extraction

INTRODUCTION

Textile industry of Tamil Nadu is the forerunner in industrial development and in providing massive employment in the state. Also, the state textile industry has a significant presence in the National economy. The 893 large and medium textile mills and 792 small units are located in Tamil Nadu which provides employment for >5 lakh labours.

Garment industry in Tirupur, Tamil Nadu plays an important role in Indian economy. Quality inspection is an important activity in textile industry for fabric manufactures because textile industry working towards just in time delivery (Chellasamy and Karuppaiah, 2005). So, they concentrated on higher quality product and improved productivity to meet customer satisfaction and to reduce the costs associated with the quality. Inspection of faults is a quality control process which aims at identifying and locating defects of fabric (Zhang *et al*., 2011). Manual inspection is a traditional means which helps for instant correction of small defects but due to fatigue and tiredness fine defects are often undetected, so the accuracy of manual inspection is not enough and also it is time consuming. Neural networks play an important role in identifying the defects in textiles. There are two main stages namely training stage and testing stage (Chandra *et al*., 2010). Fabric images should be clear and focused to obtain sharp pixels. In addition, by applying a correct fine-tuning for lighting settings, researchers can produce a good image with minimal loss in clarity while the time and complexity of processing operations will be avoided as well. Actually, it is not easy due to the expected vibration during the running of weaving machines. In addition, as fabric units (threads) are orthogonally set, we should keep the same property in the acquired fabric image (Cheng and Weidong, 2008; Ma, 2007). Automatic fabric inspection systems are designed to increase the accuracy, consistency and speed of defect detection in fabric manufacturing process to reduce labor costs, improve product quality and increase manufacturing efficiency (Lu and Zhang, 2007; Arivazhagan *et al*., 2006). Texture classification process involves two phases, the learning phase and the recognition phase. In the learning phase, the target is to build a model for the texture content of each texture class present in the training data which generally comprises of images with known class labels (Arivazhagan and Ganesan, 2003). The texture content of the training images

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is captured with the chosen texture analysis method which yields a set of textural features for each image. In the production life cycle, early detection of defects can reduce the cost impact of a defect (Newman and Jain, 1995). The solution to this problem is automated inspection of fabric defect which is used to improve fabric quality and reduce labor costs.

QUALITY OF FABRICS

Products in the market claims its quality, fabrics also have their own quality. If the fabric quality is better, the producer expects more sales and the proprietor fix higher price. So, the manufacturer always interested in producing highest quality fabrics within short time. Till now the process of identification of defects is done manually whether it is a handloom or machine weaved. It is proved that the highest fabric inspector is capable of identifying up to 70% of defects only, the remaining 30% of defects remains unidentified. These factors lead to the need for an automated inspection system which is the objective of this study.

DEFECTS IN FABRICS

The textile fabric portion has not met the requirement or an attribute of a fabric is known as defect which leads to customer dissatisfaction (Lu and Zhang, 2007). There are many types of defects occur like hole, scratch, fly yarn, slub, knot, dirty spot, cracked point, etc. during manufacturing or weaving. If these defects are not detected properly, it will affect the production process massively. In this study, researchers are concentrated four types of defects namely hole, stain, warp float and weft float. The occurrence of cut or hole. Oil or other stain is spot defects of oil, rust and grease. A float is the improper interlacement of warp and weft threads in the fabric.

PROPOSED APPROACH

The images of woven fabric without defect and with the above four types of defects are captured and then processed. Images with no defect, hole, stain, warp float and weft float are considered for inspection. The proposed approach consists of four main steps: image acquisition, preprocessing, feature extraction and defect detection (Fig. 1).

Image acquisition: The most essential parameter in image acquisition is the resolution. The resolution can be referred either by the size of one pixel or the number of pixels per inch (ppi). The term dots per inch (dpi) are commonly used than ppi. The image resolution is responsible for demonstrating the statistical features of the image. The lower the resolution, less information is saved about the image and cannot show significant difference with respect to neighboring area. The higher the resolution, more information is saved but it requires larger memory size to store. As human vision is approximately 300 dots per inch, the scanning of fabric images in the study begins from 300 dpi resolutions and will increase the resolution by a step of 100 dpi. The image acquisition is performed by different types of camera like CCD (Charged Coupled Device), CMOS (Complementary Metal Oxide Semiconductor), digital camera, etc. The illumination and natural sources of light may affect the image. The suitable resolution which provides higher detection rate for the above four types of defects is 1000 dpi (Fig. 2).

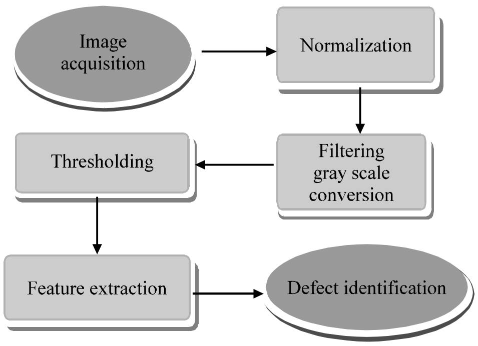


Fig. 1: Proposed approach of the system

Image preprocessing: The aim of pre-processing is an improvement of the image data to enhance image features relevant for further processing and analysis task. The image obtained from CCD camera is resized using interpolation technique. Interpolation technique is used to calculate the unknown pixel value by using the known pixel values. Interpolation techniques are grouped into two categories: adaptive and non-adaptive. Adaptive methods change depending on what they are interpolating whereas non-adaptive methods treat all pixels equally. In the study, Bilinear Interpolation Method is used this method operates on the closest 2×2 neighborhood of known pixel values surrounding unknown pixel. It then takes a weighted average of these four pixels to arrive the final interpolated value. The resulting images are much smoother looking images than nearest neighbor method (Fig. 3):

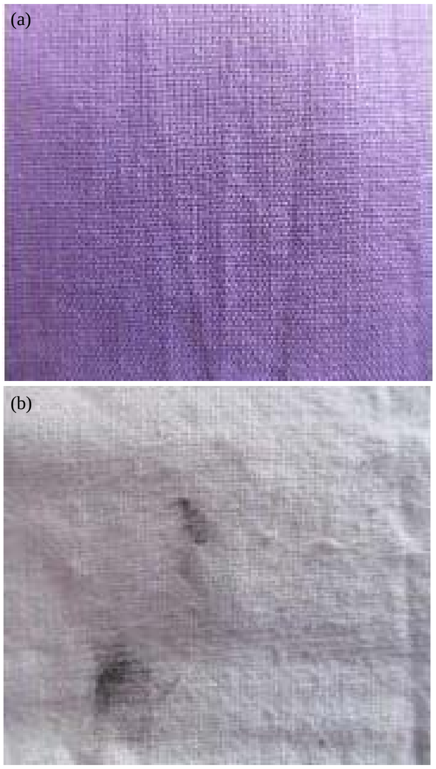


Fig. 2: a) Defect free and b) defected image

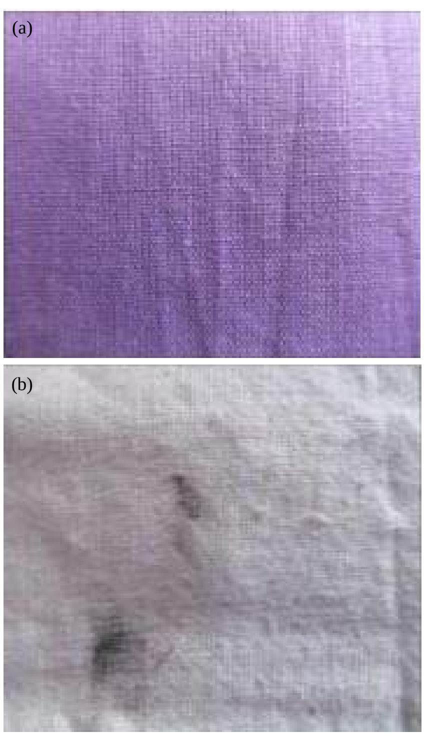
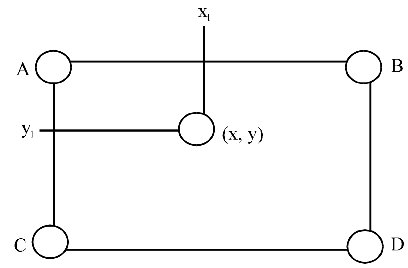


Fig. 3: a) Defect free and b) defected normalized image



$$(1-x_1)(1-y_1)A+x_1(1-y_1)B+y_1(1-x_1)C+x_1y_1D \quad (1)$$

After resizing the image, the noise is removed from the image by using Gaussian filtering techniques. The two dimensional Gaussian filter can be expressed as:

$$G(x,y)=\frac{1}{\sqrt{2\pi\sigma}}\exp\left(-\frac{x^2+y^2}{2\sigma^2}\right) \quad (2)$$

where, σ^2 is the variance of gaussian filter. The one dimensional Gaussian filter can be expressed as:

$$G(x,y)=\frac{1}{\sqrt{2\pi\sigma}}\exp\left(-\frac{x^2}{2\sigma^2}\right) \quad (3)$$

When Gaussian filter is used for noise suppression, a large filter variance is effective in smoothing out noise (Fig. 4).

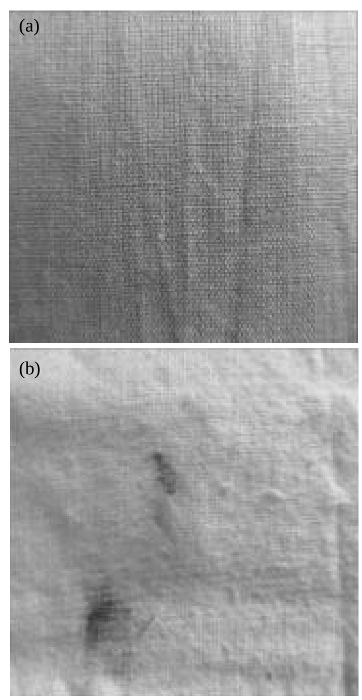


Fig. 4: a) Defect free and b) defected filtered gray image

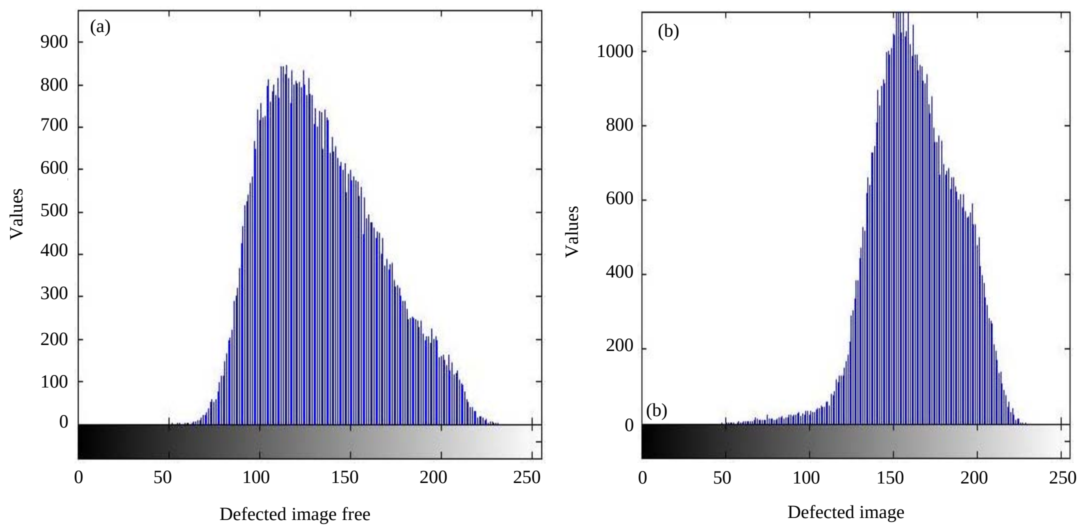


Fig. 5: a) Histogram Defect free and b) defected of image

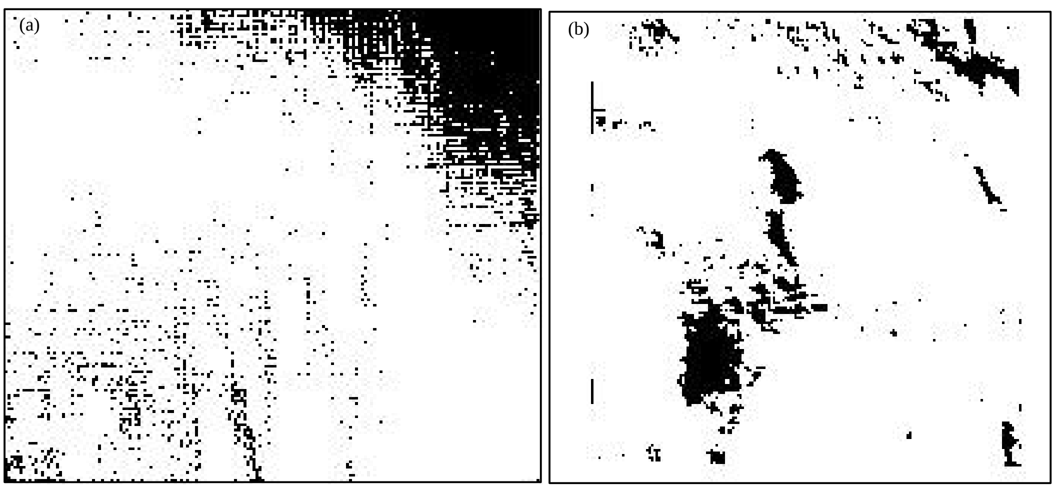


Fig. 6: a) Defect free and b) defected binary image

FEATURE EXTRACTION

In the inspection system, the original digital image is converted into to gray scale image. Histogram process has been used to calculate threshold value of grayscale image. Based on the threshold value the grayscale image is converted into binary image. From this binary image the following attributes are calculated:

- Area of faulty portion
- Number of objects
- Shape factor
- Mean
- Variance

These attributes are used as input set to the neural network to train the net in order to identify the defects (Fig. 5 and 6).

IDENTIFYING DEFECT USING NEURAL NETWORKS

This study proposes a multi-layer neural network consists of an input layer, two hidden layer and output layer. First hidden layer consists of 20 neurons and second hidden layer consists of 5 neurons. First neuron is for hole type fault, second neuron is for stain type fault, third neuron is for warp float type fault, fourth neuron is for weft float type fault and the fifth neuron is for no defect. The output layer is to produce target outputs as

[{1 0 0 0 0}, {0 1 0 0 0},{0 0 1 0 0},{0 0 0 1 0}, {0 0 0 0 1}]. The network is trained by >100 defect and defect free images. The weights are trained using Back Propagation algorithm.

The same input is tested with fuzzy neural networks. If researchers compare the output of fuzzy neural networks with neural networks, fuzzy neural networks consumes less time to execute and produces high accuracy of output.

Neural network simulates the input set after calculating input set and identify defect of image as an actual output. So, this system is simple and successfully minimizes inspection time, produces high accuracy than manual inspection system.

EXPERIMENTS AND RESULTS

The inspection system captures fabric images by acquisition device (digital camera) and passes the image to the computer. Initially, the inspection system normalize the image using interpolation methods, removes the noise then convert the image into gray scale image then into binary image by thresholding techniques. The system then calculates area of faulty portion, number of objects and shape factor of the converted binary image. These attributes of binary image is given as an input to the neural net. The neural network uses Log Sigmoid algorithm as transfer function. Mean of sum of squares of the network weights and biases is used for performance function. The fabric has hole type fault, the target output of fault pattern is 1 and remaining patterns are 0. The system is successful 89% in identifying hole fault accurately, 92% in identifying stain fault accurately, 90% in identifying warp float fault accurately and 90% in identifying weft float fault accurately. The total performance of the system is 90% accurately in identifying all four types of faults.

CONCLUSION

In this study, a new Intelligent Fabric Defect Inspection System was demonstrated. The problem is to create the necessary image analysis and identification methods to accurately, quickly locate and identify the defects in the fabric. The system for inspection of fabric defect detects 90% accurately. The results obtained by the proposed system indicate that a reliable fabric inspection system can be created for textile industries.

REFERENCES

Arivazhagan, S. and L. Ganesan, 2003. Texture classification using wavelet transform. Pattern Recog. Lett., 24: 1513-1521.

Arivazhagan, S., L. Ganesan and S. Bama, 2006. Fault segmentation in fabric images using Gabor wavelet transform. Mach. Vision Applic., 16: 356-363.

Chandra, J.K., P.K. Banerjee and A.K. Dattab, 2010. Neural network trained morphological processing for the detection of defects in woven fabric. J. Text. Inst., 101: 699-706.

Chellasamy, P. and K. Karuppaiah, 2005. An analysis of growth and development of textile industry in India. http://www.share-pdf.com/f3a23f6000794d039327467aef6281e9/growth%20pooja.pdf.

Cheng, Y.K. and Y. Weidong, 2008. Clothing defect detection system based on image processing technology. Comput. Syst. Applic., 10: 7-10.

Lu, Y. and J.M. Zhang, 2007. Fabric defect detection method based on image distance difference. Micro-Comput. Inform., 23: 306-308.

Ma, H.L., 2007. Fabric defect detection analysis and design based on image recognition. Master's Thesis, Beijing University of Technology, China.

Newman, T.S. and A.K. Jain, 1995. A survey of automated visual inspection. Comput. Vis. Image Understand., 61: 321-262.

Zhang, Y.H., C.W.M. Yuen, W.K. Wong and C.W. Kan, 2011. An intelligent model for detecting and classifying color-textured fabric defects using genetic algorithms and the Elman neural network. Textile Res. J., 81: 1772-1787.