Automated Textile Defect Recognition System Using Computer Vision and Artificial Neural Networks

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***Abstract*—**Least Development Countries (LDC) like Bangladesh, whose 25% revenue earning is achieved from Textile export, requires producing less defective textile for minimizing production cost and time. Inspection processes done on these industries are mostly manual and time consuming. To reduce error on identifying fabric defects requires more automotive and accurate inspection process. Considering this lacking, this research implements a Textile Defect Recognizer which uses computer vision methodology with the combination of multi-layer neural networks to identify four classifications of textile defects. The recognizer, suitable for LDC countries, identifies the fabric defects within economical cost and produces less error prone inspection system in real time. In order to generate input set for the neural network, primarily the recognizer captures digital fabric images by image acquisition device and converts the RGB images into binary images by restoration process and local threshold techniques. Later, the output of the processed image, the area of the faulty portion, the number of objects of the image and the sharp factor of the image, are feed backed as an input layer to the neural network which uses back propagation algorithm to compute the weighted factors and generates the desired classifications of defects as an output.

***Keywords*—**Computer vision, image acquisition device, machine vision, multi-layer neural networks.

I. Introduction

ALL textile industries aim to produce competitive fabrics. The competition enhancement depends mainly on productivity and quality of the fabrics produced by each industry. In the textile sector, there have been an enlarge amount of losses due to faulty fabrics.

In the least developed countries like Bangladesh, most defects arising in the production process of a textile material are still detected by human inspection. The work of inspectors is very tedious and time consuming. They have to detect small details that can be located in a wide area that is moving through their visual field. The identification rate is about 70%. In addition, the effectiveness of visual inspection decreases quickly with fatigue. Digital image processing techniques have been increasingly applied to textured samples analysis over the last ten years [1]. Wastage reduction through accurate and early stage detection of defects in fabrics is also an important aspect of quality improvement. Table I from [2] summarize the comparison between human visual inspection and automated inspection. Also, it has been stated in [3] that price of textile fabric is reduced by 45% to 65% due to defects.

In textile sectors, different types of faults are available i.e. hole, scratch, stretch, fly yarn, dirty spot, slub, cracked point, color bleeding etc; if not detected properly these faults can affect the production process massively. Proposed textile defect recognizer mainly detects four types of faults that are hole, scratch, fresh as no fault and remaining faults as other fault.

TABLE I
VISUAL INSPECTION VERSUS AUTOMATED INSPECTION

Inspection Type	Visual	Automated
Fabric Types	100%	70%
Defect Detection Rate	70%	80%+
Reproducibility	50%	90%+
Objective Defect Judgment	50%	100%
Statistics Ability	0%	95%+
Inspection Speed	30 m/min	120 m/min
Response Type	50%	80%
Information Content	50%	90%+
Information Exchange	20%	90%+

In this paper, the textile defect recognizer is viewed as a real-time control agent that transforms the captured digital image into adjusted resultant output and operates the automated machine (i.e. combination of two leaser beams and production machine), illustrated in Fig. 1. In this proposed system as the recognizer identifies a fault of any

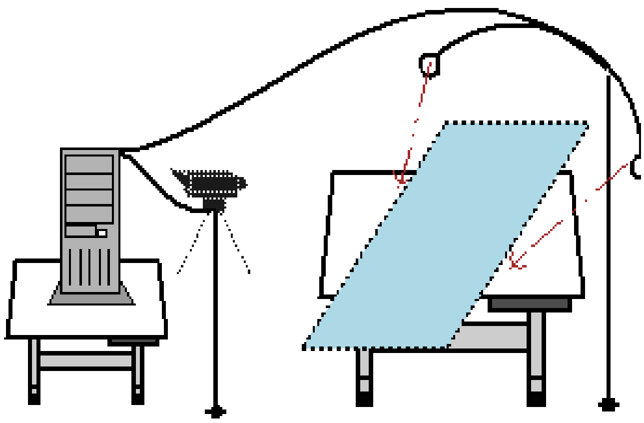


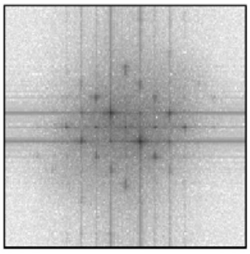
Fig. 1 Real-time Environment of Textile Defect Recognition

type mentioned above, will immediately recognize the type of fault which in return will trigger the laser beams in order to display the upper offset and the lower offset of the faulty portion. The upper offset and the lower offset implies the 2 inches left and 2 inches right offset of faulty portion. This guided triggered area by the laser beans will indicate the faulty portion that needs to be extracted from the roll. After cutting the desired portions of fabric, textile defect recognizer resumes its operation.

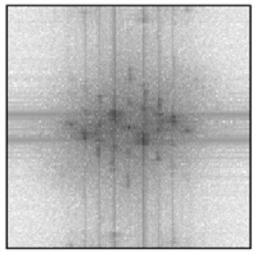
The objective of the paper is to develop an automated textile defect recognize system based on computer vision methodology and adaptive neural networks. This paper mainly focuses on combine engine of image processing and artificial neural networks in textile industries research arena.

II. Literature Review

Machine vision automated inspection system for textile defects has been in the research industry for a longtime [8], [9]. Recognition of patterns independent of position, size, brightness and orientation in the visual field has been the goal of much recent work. However, there is still a lack of work in machine vision automated system for recognizing textile defects using AI. A neural network pattern recognizer was developed in [10]. Fully connected three multilayer percetron network was used to identify different sizable objects. The input of this network is seven standardized invariant moment and the weights are trained using back propagation. Since the network uses standardized moments as input, neural net similar to this requires lots of iteration to train. The research takes directly input as binary images as a result no preprocessing of image is performed. Today's automated fabric inspection systems are based on adaptive neural networks. So instead of going through complex programming routines, the users are able to simply scan a short length of good quality fabric to show the inspection system what to expect. This coupled with specialized computer processors that have the computing power of several hundred Pentium chips makes these systems viable [20]. Three state-of-the-art fabric inspection systems are – BarcoVision's Cyclops, Elbit Vision System's I-Tex and Zellweger Uster's Fabriscan. These systems can be criticized on grounds that they all work under structured environments – a feat that is almost non-existent in LDC countries. There are some works in [11] based on the optical Fourier transform directly obtained from the fabric with optical devices and a laser beam. Digital image processing techniques have been increasingly applied to textured samples analysis over the last ten years. Several authors have considered defect detection on textile materials. Kang et al. [12], [13] analyzed fabric samples from the images obtained from transmission and reflection of light to determine its interlacing pattern. Wavelets had been applied to fabric analysis by Jasper et al. [14], [15]. Escofet et al. [16], [17] have applied Gabor filters (wavelets) to the automatic segmentation of defects on non-solid fabric images for a wide variety of interlacing patterns. Millán and Escofet [18] introduced Fourier-domain-based angular correlation as a method to recognize similar periodic patterns, even though the defective fabric sample image appeared rotated and scaled. Recognition was achieved when the maximum correlation value of the scaled and rotated power spectra was similar to the autocorrelation of the power spectrum of the pattern fabric sample. If the method above was applied to the spectra presented in Fig. 2(a) and 2(b), the maximum angular correlation value would be considerably lower than the autocorrelation value of the defect free fabric spectrum. Fourier analysis does not provide, in general, enough information to detect and segment local defects. Electronic textiles (e-textiles) are fabrics with interconnections and electronics woven into them. The electronics consist of both processing and sensing



(a) Power spectrum of the pattern fabric sample



(b) Power spectrum of the defective fabric sample

Fig. 2

elements, distributed throughout the fabric. Thomas Martin et al. [19] describe the design of a simulation environment for electronic textiles (e-textiles) but having a greater dependence on physical locality of computation. The current status of the simulation environment for e-textiles and present results generated by the environment and associated prototypes for two applications, a large-scale acoustic beamforming fabric for locating vehicles and a pair of pants for classifying and analyzing wearer motions. Gabor filter is a widely feature extraction method, especially in image texture analysis. The selection of optimal filter parameters is usually problematic and unclear. Yimiing et al. [21] analyze the filter design essentials and proposes two different methods to segment the Gabor filtered multi-channel images. The first method integrates Gabor filters with labeling algorithm for edge detection and object segmentation. The second method uses the K-means clustering with simulated annealing for image segmentation of a stack of Gabor filtered multi-channel images. But the classic Gabor expansion is computationally expensive and since it combines all the space and frequency details of the original signal, it is difficult to take advantage of the gigantic amount of numbers. Our research had reviewed other image processing works that are combination of histogram analysis, binarization with threshold and neural networks. But most of these works are performed in controlled environment by not taking consideration of the economic feasibility and customizability for industrial use.

III. Model Presentation

The system design of textile defect recognizer, which mentioned into this paper, is illustrated in Fig. 3. The proposed system can be a competitive model for

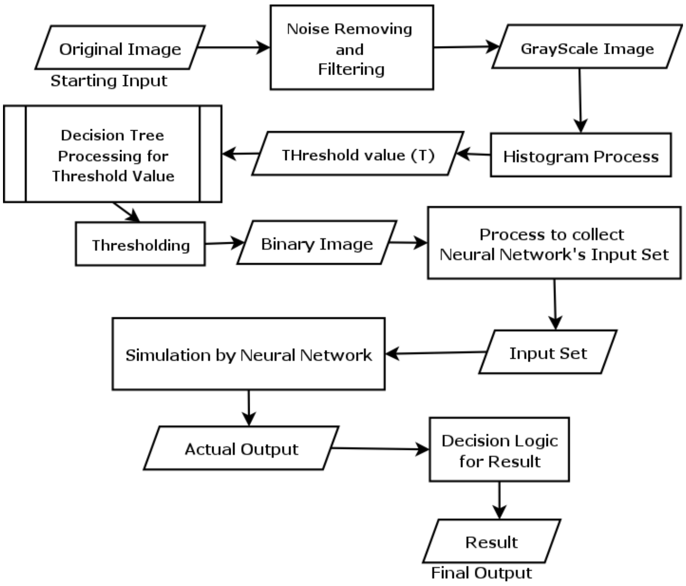


Fig. 3 System Design of Textile Defect Recognizer

recognizing textile defects in real world. Base on the research, the proposed system design is separated into two parts. The first part of our research processes the images to fit for the input layer set of the neural network. The second part of the paper uses the input set to recognize the defects and adapts the neural net.

A. Processing Input Using Computer vision methodology:

In our recognition system, the original digital (RGB) image is converted into grayscale image through noise removing and filtering techniques (restoration process). As image processing is costly, for this reason, adaptive median filter algorithm has been used as spatial filtering for minimizing time complexity and maximizing performance [4]. After restoration processing, histogram process has been used to calculate threshold value of grayscale image. In our proposed system, the most important key point is the decision tree processing in order to achieve the threshold value. As we know that there have been different types of textile fabrics and also different types of defects in textile industries, so local thresholding was used based on decision tree process. The proposed decision tree process has been developed based on an empirical data set. An example is provided in Fig. 4, the fabric shown is faulty fabric (Scratch). And the intensity histogram of specific fabric is shown in Fig. 5, where we can identify the

Fig. 4 Original Faulty (Scratch) Fabric

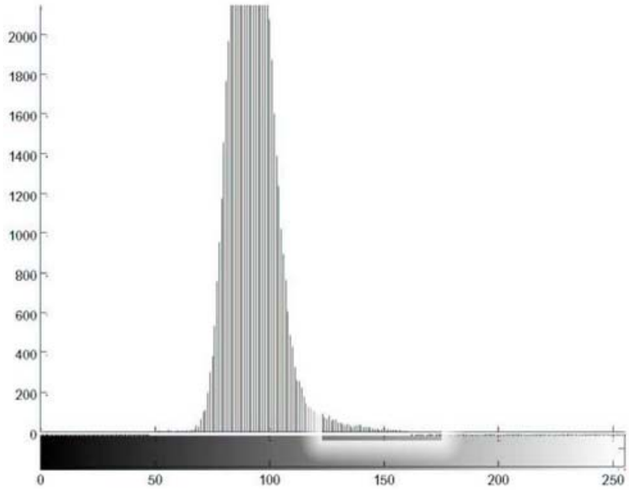


Fig. 5 Histogram of Faulty (Scratch) Fabric

threshold value (T) at greater then 120 and less than 170. Similar example is in Fig. 6, the fabric is faulty fabric

Fig. 6 Original Faulty (Hole) Fabric

(Hole) and the histogram of this is shown in Fig. 7. From the intensity histogram of the fabric (Fig. 7) we can identify

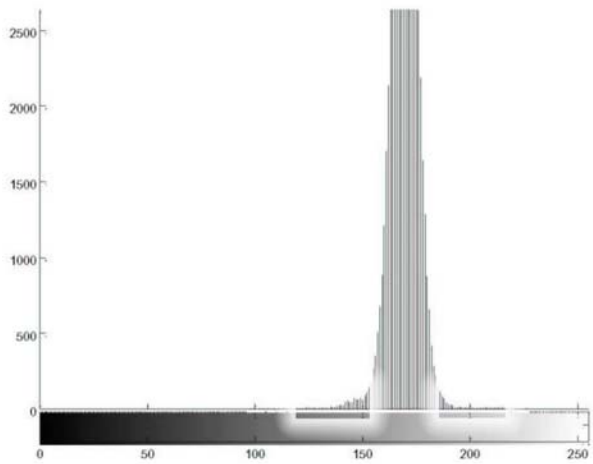


Fig. 7 Histogram of Faulty (Hole) Fabric

threshold value (T) at less then 155 and also threshold value (T) at greater then 200. Due to different threshold values to different pattern of faults, this proposed paper could not generalize a specific threshold value (T) for all types of fabrics. As a result, in order to achieve a consistent and precise threshold value, the histogram outputs of 200 images were taken to develop the decision tree as Fig. 8. Base on the threshold value achieved from the decision tree,

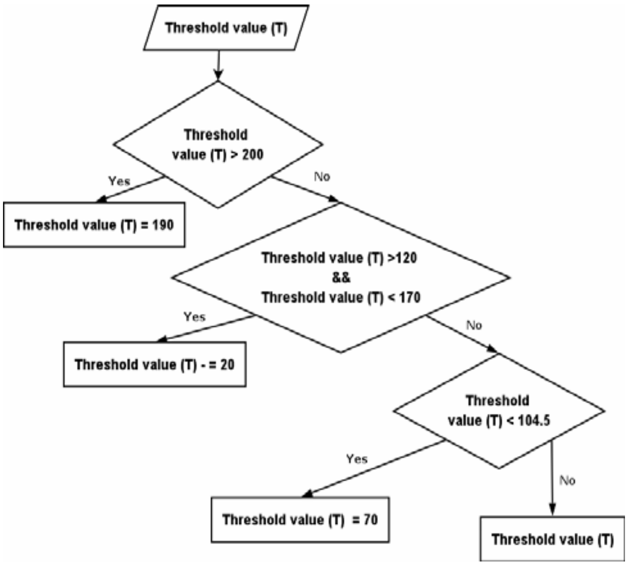


Fig. 8 Decision Tree for Threshold Value (T)

grayscale image is converted into binary image using local thresholding technique. From this binary image we calculate the following attributes:

i) ***Area of the faulty portion:*** calculates the total defected area of an image.

ii) ***Number of objects:*** uses image segmentation to calculate the number of labels in an image.

ii) ***Sharp factor:*** distinguishes a circular image form a noncircular image. Sharp Factor uses the area of a circle to identify the circular portions of the fault.

These three attributes are used as input sets to adapt the neural net through training set in order to recognize expected defects.

B. Recognizing Defect using Neural Networks:

This paper proposes a multi-layer fully connected neural network consists of an input layer, two hidden layers and an output layer as illustrates in Fig. 9. In the neural networks, first hidden layer has 40 neurons and second hidden layer has 4 neurons. 1st neuron of 2nd hidden layer is for Hole type fault, 2nd neuron of 2nd hidden layer is for Scratch type fault, 3rd neuron of 2nd hidden layer is for Other type fault and 4th neuron of 2nd hidden layer is for No fault (fresh image). Each layer produces any value of range 0 ~ 1. The output layer is to produce target outputs as [{1 0 0 0}, {0 1 0 0}, {0 0 1 0}, {0 0 0 1}]. The network is trained by a set (more 200 images) of pre-classified defect and fresh digital fabric images. The weights are trained using resilient back propagation algorithm. Resilient back propagation is generally much faster than the standard steepest descent algorithm. It also has the nice property that it requires only a modest increase in memory requirements. We do need to store the update values for each weight and bias, which is equivalent to storage of the gradient [6], [7].

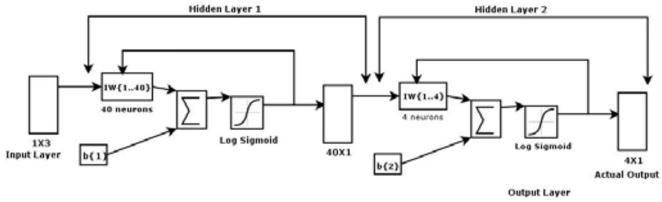


Fig. 9 Design of Feed Forward Back propagation Neural Network

Training time of neural networks is infinity where network goal is 10^{-5}. After calculating input set, neural network simulates the input set and recognizes defect of image as an actual output. From the resultant output, our proposed system can release final result by the help of decision logic.

So, this system is a simple engine based on computer vision methodology and neural networks in textile industries sector. Efficiency is one of the key points of this system as a result all the algorithms applied on the system is aggressively tested by time and space complexity. The system will successfully minimize inspection time than other manual or automated inspection based system.

IV. Approach and Result Analysis

In our experiment, the textile defect recognizer captures digital fabric images, as shown in Fig. 4, by image acquisition device i.e. digital camera and passes the image through serial port to the computer. Initially, the recognizer removes noise and than applies adaptive filter technique to converts digital (RGB) image to grayscale image, illustrated in Fig. 10. After restoration processing, the textile defect

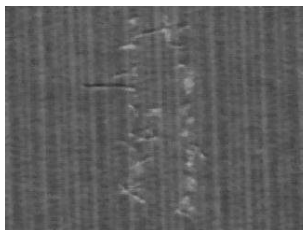


Fig. 10 Grayscale Image

recognizer uses local thresholding technique in order to convert grayscale image into binary image, illustrated in Fig. 11 where black border is used for better understanding.

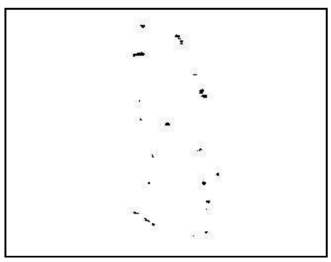


Fig. 11 Binary Image

After successful accomplishment of local thresholding, the recognizer than calculates the area of fault, number of objects of image and sharp factor of the converted binary image (shown in Table II). The defect recognizer takes calculated area of faulty portion, number of objects and sharp factor of that binary image as an input set of the neural networks. In this paper, applied neural network uses Log Sigmoid algorithm as transfer function. Mean of sum of squares of the network weights and biases algorithm is used for performance function. Widrow-Hoff weight/biases algorithm is used as learning function [5]. Learning rate of neural networks is 0.01 and network goal is 10^{-5}. For the given image as shown in Fig. 4, the target output set of neural network for training is given in Table III. Since the fabric has Scratch type fault, the target output of Fault (Scratch) pattern is 1 and remaining patterns are 0. After adapting the input set by the trained data, the neural network generates the corresponding output illustrated in Table IV. Since the input image was Scratch type defect, correspondingly we can observe the resultant output values of Scratch Fault is higher (close to 1) than the other faults. According to the proposed model, this recognizer than triggers the laser beams to the lower leftmost offset and higher rightmost offset from the identified faulty area. The textile defect recognizer applies the following training set (Table V) to adapt the neural net. After triggering the leaser beams, the recognizer moves the leaser beams by generating angle positions to the upper offset and lower offset of the fault area, and turns offs the production machine.

TABLE II
NEURAL NETWORK INPUT SET

Area	No of Objects	Sharpe Factor
76700	1	0.77389

TABLE III
NEURAL NETWORK TARGET OUTPUT SET

Fault(Hole)	Fault(Scratch)	Fault(Other)	No Fault
0	1	0	0

TABLE IV
NEURAL NETWORK ACTUAL OUTPUT SET OF INPUT IMAGE

Fault(Hole)	Fault(Scratch)	Fault(Other)	No Fault
0.2587	0.9490	0.2801	0.1486

TABLE V
TRAINING SET OF NEURAL NETWORKS

Area	No of Objects	Sharp Factor
76721	1	0.76952
76636	1	0.77211
76638	1	0.77211
76744	1	0.77433
76661	1	0.77369
72362	2	0.45776
23190	1	0.26801
72424	1	0.49566
75446	1	0.76123
76620	1	0.77426
76237	1	0.77467
76798	1	0.77291
76717	1	0.77317
76743	1	0.77416
76729	1	0.77416
76673	1	0.77361
76600	1	0.77378
76722	1	0.77389
76659	1	0.77411
13824	1	0.77349
72282	1	0.060447
72282	1	0.53926
40475	1	0.47908
23324	2	0.43865
40477	2	0.26698
40351	2	0.29955
76637	2	0.2743
76683	1	0.32209
72268		0.5698

The performance of the recognizer is concluded in Fig. 12. We can observe from our performance curve that the recognizer is successful 72% in identifying hole classified faults accurately, 65% in identifying scratch classified faults, 86% in identifying other classified faults and 83% identifying no fault defects. The total performance of the system, which includes identifying all the faults; our system performs 77% accurately in identifying all four patterns of faults (shown as resultant performance in Fig. 12).

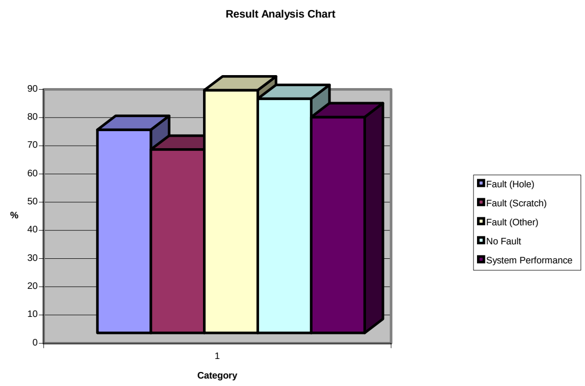


Fig. 12 Individual parameters and Resultant performance Experiment

V. SUMMARY AND FUTURE WORK

It has been demonstrated that Textile Defect Recognition System is capable of detecting fabrics' defects with more accuracy and efficiency. In the research arena, our system tried to use the local threshold technique without the decision tree process. Since our recognizer deals with different types of faults and fabrics, therefore the recognition system cannot access a general approach for local thresholding technique.

The proposed research observes that there are a large percentage of misclassifications using Widrow-Hoff learning algorithm and Resilient back propagation training algorithm to recognize the defects or non-defects of fabrics for the variations of area of faulty portion, number of objects and sharp factor. As a result, a variation of performance is noticed, in identifying other faults than hole and scratch faults .Our recognizer can detect few amounts of multi-colored defect fabrics. There have many types of defects, which are not within the scope of the above recognition system.

REFERENCES

[1] M. Ralló, M. S. Millán, J. Escofet, "Wavelet based techniques for textile inspection", *Opt. Eng.* 26(2), 838-844 (2003)

[2] R. Meier, "Uster Fabriscan, The Intelligent Fabric Inspection," [Online document], cited 20 Apr. 2005], Available HTTP: http://www.kotonline.com/english_pages/ana_basliklar/uster.asp

[3] R. Stojanovic, P. Mitropulos, C. Koulamas, Y. A. Karayiannis, S. Koubias, and G. Papadopoulos, "Real-time Vision based System for Textile Fabric Inspection", *Real-Time Imaging*, vol. 7, no. 6, 2001, pp. 507–518.

[4] R. C. Gonzalez, R. E. Woods, S. L. Eddins, "Digital Image Processing using MATLAB", ISBN 81-297-0515-X, 2005, pp. 76-104,142-166,404-407

[5] M. T. Hagan, H. B. Demuth, M. Beale, "Neural Network Design", ISBN 981-240-376-0, 2002, part 2.5, 10.8

[6] Riedmiller, M., and H. Braun, "A direct adaptive method for faster backpropagation learning: The RPROP algorithm", Proceedings of the IEEE International Conference on Neural Networks, 1993.

[7] Neural Network Toolbox, "MATLAB –The Language of Technical Conputing", [CD Document], Version 7.0.0.19920(R14), 2004

[8] B. G. Batchelor and P. F. Whelan, "Selected Papers on Industrial Machine Vision Systems," *SPIE Milestone Series,* 1994.

[9] T. S. Newman and A. K. Jain, "A Survey of Automated Visual Inspection," *Computer Vision and Image Understanding,* vol. 61, 1995, pp. 231–262.

[10] H Zhang, J. Guan and G. C. Sun, "Artificial Neural Network-Based Image Pattern Recognition", ACM 30th Annual Southeast Conference, 1992

[11] Ciamberlini C., Francini F., Longobardi G., Sansoni P., Tiribilli, B. "Defect detection in textured materials by optical filtering with structured detectors and selfadaptable masks", *Opt. Eng.* 35(3), 838-844 (1996)

[12] Kang T.J. et al. "Automatic Recognition of Fabric Weave Patterns by Digital Image Analysis", *Textile Res. J.* 69(2), 77-83 (1999)

[13] Kang T.J. et al. "Automatic Structure Analysis and Objective Evaluation of Woven Fabric Using Image Analysis", *Textile Res. J.* 71(3), 261-270 (2001)

[14] Jasper W.J., Garnier S.J., Potlapalli H., "Texture characterization and defect detection using adaptive wavelets", *Opt. Eng.* 35(11), 3140-3149 (1996)

[15] Jasper W.J., Potlapalli H., "Image analysis of mispicks in woven fabric", *Text. Res.J.* 65(1), 683-692 (1995)

[16] Escofet J., Navarro R., Millán M.S., Pladellorens J., "Detection of local defects in textile webs using Gabor filters", in "*Vision Systems: New Image Processing Techniques*" Ph. Réfrégier, ed. Proceedings SPIE vol. 2785, 163-170 (1996)

[17] Escofet J., Navarro R., Millán M.S., Pladellorens J., "Detection of local defects in textile webs using Gabor filters", *Opt. Eng.* **37**(8) 2297-2307 (1998)

[18] Millán M.S., Escofet J., "Fourier domain based angular correlation for quasiperiodic pattern recognition. Applications to web inspection", *Appl. Opt.* 35(31), 6253-6260 (1996)

[19] T. Martin, M. Jones, J. Edmison, T. Sheikh and Z. Nakad,"Modeling and Simulating Electronic Textile Applications", LCTES, USA, 2004

[20] A. Dockery, "Automatic Fabric Inspection: Assessing the Current State of the Art," [Online document], 2001, [cited 29 Apr. 2005], Available HTTP:

[21] Y. Ji, K. H. Chang and CC. Hung, "Efficient Edge Detection and Object Segmentation Using Gabor Filters", ACMSE, USA, 2004.