A Suitable Neural Network to Detect Textile Defects

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Abstract. 25% of the total revenue earning is achieved from Textile exports for some countries like Bangladesh. It is thus important to produce defect free high quality garment products. Inspection processes done on fabric industries are mostly manual hence time consuming. To reduce error on identifying fabric defects requires automotive and accurate inspection process. Considering this lacking, this research implements a Textile Defect detector. A multi-layer neural network is determined that best classifies the specific problems. To feed neural network the digital fabric images taken by a digital camera and converts the RGB images are first converted into binary images by restoration process and local threshold techniques, then three different features are determined for the actual input to the neural network, which are the area of the defects, number of the objects in a image and finally the shape factor. The develop system is able to identify two very commonly defects such as Holes and Scratches and other types of minor defects. The developed system is very suitable for Least Developed Countries, identifies the fabric defects within economical cost and produces less error prone inspection system in real time.

Keywords: Textile defects, threshold decision tree, multi-layer neural networks, resilient back propagation, cross validation.

1 Introduction

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 1 [2] summarizes the comparison between human visual inspection and automated inspection. Also, it has been observed [3] that price of textile fabric is reduced by 45% to 65% due to defects.

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Table 1. 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 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.

Machine vision automated inspection system for textile defects has been in the research industry for 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 list developed countries like Bangladesh.

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.1, 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 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 beam forming 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. From the literature it is clear that there exists many systems that can detect textile defects but hardly affordable by the small industries of the List Developed countries like Bangladesh.

In this paper we propose a textile defect recognizer that can detect three types of very common faults in textile production, that are hole, scratch, and other fault. An automated textile defect detector based on computer vision methodology and adaptive neural networks is built combining engines of image processing and artificial neural networks in textile industries research arena.

Here 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),

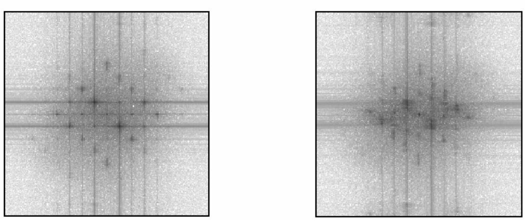

Fig. 1. Power spectrum of the pattern fabric sample (left) and the defective fabric sample (right)

In the proposed system as the recognizer identifies a fault of any 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.

2 Mythology and Implementation of the System

Major steps required to implement the proposed system is depicted in Fig. 2. The proposed system can be a competitive model for 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 focuses on the processing of the images to prepare to feed into the neural network. The second part is about building a neural network that best performs on the criteria to sort out the textile defects.

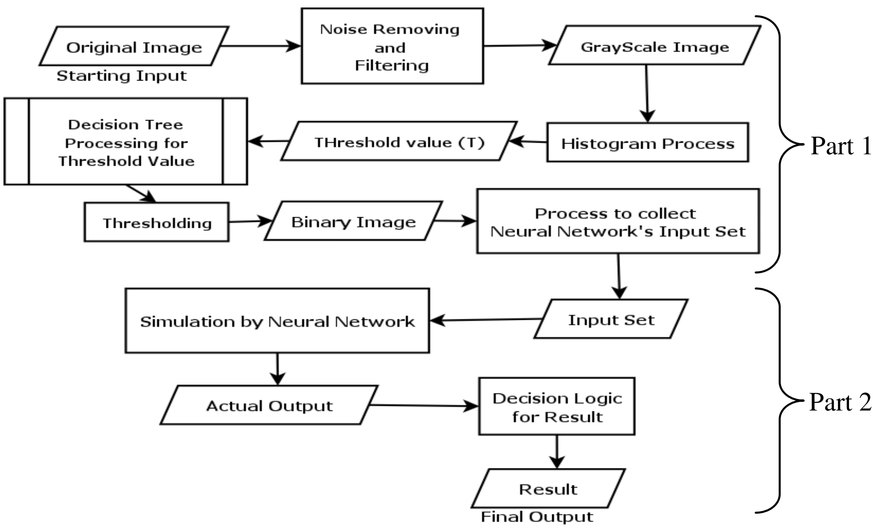

Fig. 2. Major components of the textile defect detector

2.1 Processing Textile Image for the Neural Network Input

At first the images of the fabric is captured by digital camera in RGB format (top left image in figure and figure) and passes the image through serial port to the computer. Then, noise is removed using standard techniques and an adaptive median filter algorithm has been used as spatial filtering for minimizing time complexity and maximizing performance [4] to converts digital (RGB) images to grayscale images (top middle image in Fig. 3). After restoration local thresholding technique (the process is discussed in next sub-section) is used in order to convert grayscale image into binary image (top right in Fig. 3). Finally, this binary image is used to calculate the following attributes:

1. **The area of the faulty portion:** calculates the total defected area of a image.
2. **Number of objects:** uses image segmentation to calculate the number of labels in an image.
3. **Shape factor:** distinguishes a circular image form a noncircular image. Shape 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.

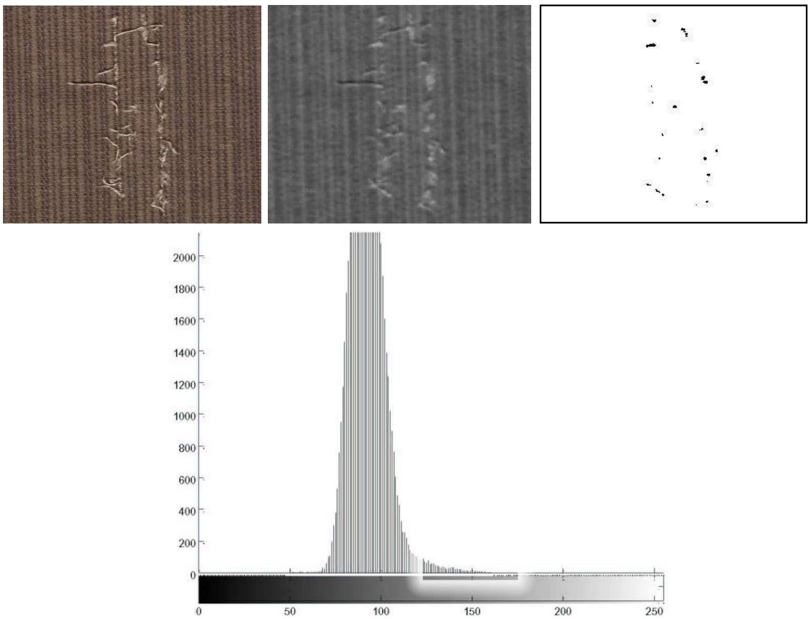

Fig. 3. Original Faulty (Scratch) Fabric (top left), gray (top middle) and binary (top right) representation and histogram (bottom) of the gray

Decision tree for threshold from gray to binary. A decision tree is constructed based on the histogram of the image in hand to convert the gray scale image in a binary representation. As we know from the problem description that there are different types of textile fabrics and also different types of defects in textile industries hence different threshold values to different pattern of faults there is no way to generalize threshold value (T) from one image for all types of fabrics. Notice this phenomenon in histograms illustrated in Fig. 3. (The identified threshold value (T) should be greater then 120 and less than 170) and Fig. 4. (The identified threshold value (T) should be greater then 155 and less then 200). A local threshold was used based on decision tree which was constricted using set of 200 image histograms of fabric data. Illustration of the decision tree is provided in Fig. 5.

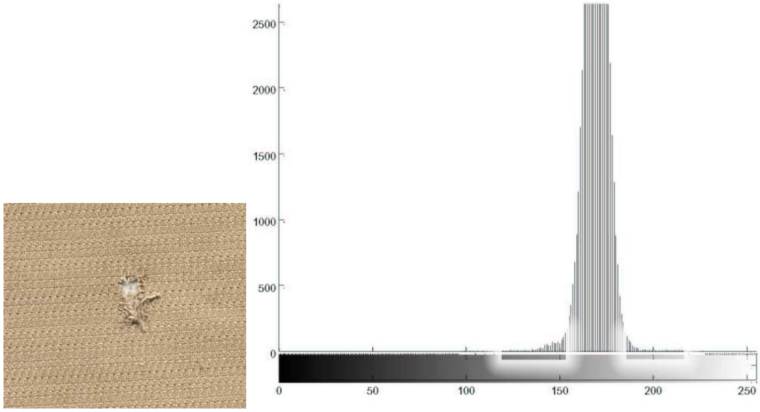

Fig. 4. Original Faulty (Hole) Fabric (left) and the histogram of the gray representation (right)

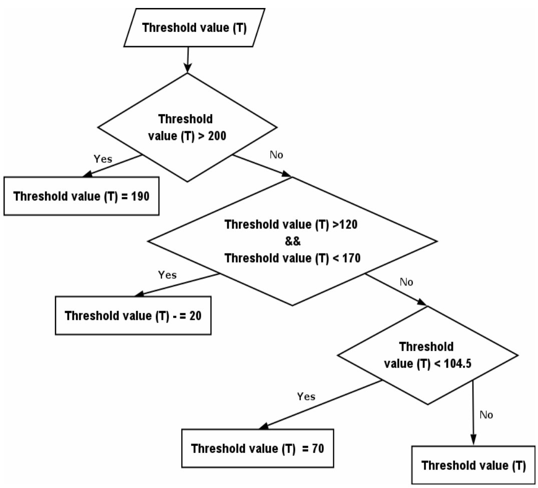

Fig. 5. Decision Tree for Threshold Value (T) to convert from gray to binary

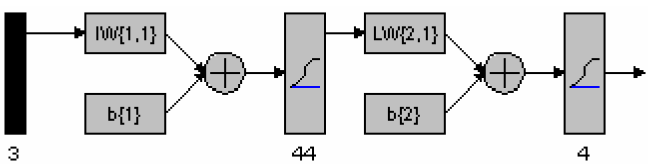

Fig. 6. Design of Feed Forward Back propagation Neural Network

2.2 The Suitable Neural Network

In search of a fully connected multi-layer neural network that will sort out the defected textiles we start with a two layer neural network (Fig. 6). Our neural network contains one hidden of 44 neurons and one output layer of 4 neurons. The neurons in the output layer is delegated as 1st neuron of the output layer is to Hole type fault, 2nd neuron of the output layer is to Scratch type fault, 3rd neuron of the output layer is to Other type of fault and 4th neuron of the output layer is for No fault (not defected fabric). The output range of the each neuron is in the range of [0 ~ 1] as we use log-sigmoid threshold function to calculate the final out put of the neurons. Although during the training we try to reach the following for the target output [{1 0 0 0}, {0 1 0 0}, {0 0 1 0}, {0 0 0 1}] consecutively for Hole type defects, Scratch type defects, Other type defects and No defects, the final output from the output layer is determined using the winner- take-all method.

To determine the number of optimal neurons in the hidden layer was the tricky part, we start with 20 neurons in the hidden layer and test the performance of the neural network on the basis of a fixed test set, and then we increase the number of neurons one by one and till 60, the number of neurons in the hidden layer is chosen based on the best performance. The error curve is illustrated in Fig. 7.

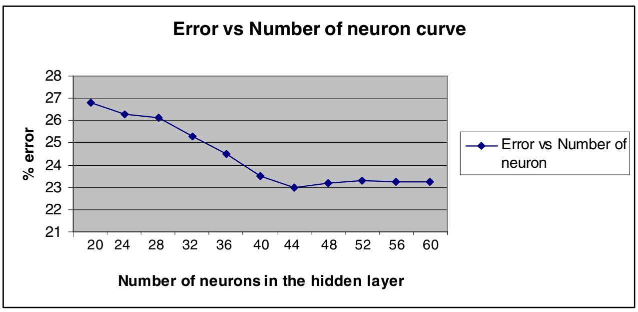

Fig. 7. Performance (in % error) carve on the neuron number in the hidden layer

The parameters used in the neural network can be summarized as:

- Training data set contains 200 images; 50 from each class.
- Test data set contains 20 images; 5 from each class
- The transfer function is Log Sigmoid.
- Performance function used is mean square error
- Widrow-Hoff algorithm is used as learning function [5] with a learning rate of .01.
- To train the network resilient back propagation algorithm [6], [7] is used. Weights and biases are randomly initialized. Initial delta is set to .05 and the maximum value for delta is set to 50, the decay in delta is set to .2.
- Training time or total iteration allowed for the neural networks to train is set to infinity as we know it is a conversable problem. And we have the next parameter to work as stopping criterion
- Disparity or maximum error in the actual output and network output is set to 10^{-5}.

3 Results and Discussions

The performance of the textile recognizer is determined based on the cross validation method. The average result is provided in Fig. 8. Here notice that the recognizer can successfully identifying Hole type faults with 72% accuracy, 65% of Scratch type faults, 86% of the Other type faults and 83% No faults accurately. The average performance of the system determining the defects in textile industry is 74.33% and the overall all performance of the system is 76.5%.

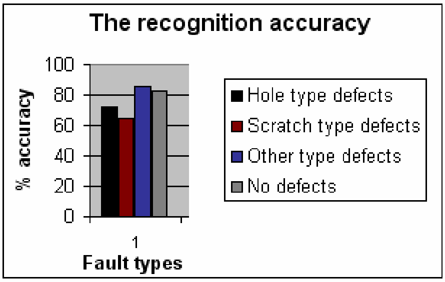

Fig. 8. The bar chart for the performance accuracy of the system

4 Conclusion

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. Here we have 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.

The system performs quite well except the problem of false negative classification, where it fails to classify the good fabric as good and marks it as faulty fabric; the future versions of the system will try to notice this problem more precisely.

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, 20041.