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

Atiqul Islam, Shamim Akhter, and Tumnun E. Mursalin

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.

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<thead>
<tr>
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<th>Visual</th>
<th>Automated</th>
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<tr>
<td>Inspection Type</td>
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<td>Fabric Types</td>
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<td>70%</td>
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<tr>
<td>Defect Detection</td>
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<td>80%+</td>
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<td>Rate</td>
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<td>Reproducibility</td>
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<td>90%+</td>
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<td>Objective Defect</td>
<td>50%</td>
<td>100%</td>
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<td>Judgment</td>
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<td>Content Exchange</td>
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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.

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 laser beams and production machine), illustrated in Fig. 1. In this proposed system as the recognizer identifies a fault of any
Millán and Escofet [18] introduced Fourier-domain-based solid fabric images for a wide variety of interlacing patterns. wavelets to the automatic segmentation of defects on non-Escofet et al. [16], [17] have applied Gabor filters been applied to fabric analysis by Jasper et al. [14], [15].

of light to determine its interlacing pattern. Wavelets had from the images obtained from transmission and reflection materials. Kang et al. [12], [13] analyzed fabric samples applied to textured samples analysis over the last ten years. 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 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. 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. 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. 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.
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 recognizing textile defects in real world. Based 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 threshold value (T) at greater than 120 and less than 170. Similar example is in Fig. 6, the fabric is faulty fabric (Hole) and the histogram of this is shown in Fig. 7. From the intensity histogram of the fabric (Fig. 7) we can identify threshold value (T) at less than 155 and also threshold value (T) at greater than 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, grayscale image is converted into binary image using local thresholding technique. From this binary image we calculate the following attributes:

- **Area of the faulty portion**: calculates the total defected area of an image.
- **Number of objects**: uses image segmentation to calculate the number of labels in an image.
- **Sharp factor**: distinguishes a circular image from 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].

**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 convert digital (RGB) image to grayscale image, illustrated in Fig. 10. After restoration processing, the textile defect 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.
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 laser beams, the recognizer moves the laser beams by generating angle positions to the upper offset and lower offset of the fault area, and turns offs the production machine.

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).

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 faults.
multi-colored defect fabrics. There are many types of defects, which are not within the scope of the above recognition system.

REFERENCES