Novel Approaches for Detecting Fabric Fault using Artificial Neural Network with K-fold Validation

Ahmed Shayer Andalib
Department of Computer Science & Engineering
Bangladesh University of Engineering & Technology
Dhaka - 1000, Bangladesh
Email: ahmed.s.andalib@gmail.com

Mohammad Raihanul Islam
Department of Computer Science & Engineering
Bangladesh University of Engineering & Technology
Dhaka - 1000, Bangladesh
Email: raihan2108@gmail.com

Asif Salekin
Department of Computer Science & Engineering
Bangladesh University of Engineering & Technology
Dhaka - 1000, Bangladesh
Email: asalekin@gmail.com

Md. Abdulla-Al-Shami
Department of Computer Science & Engineering
Bangladesh University of Engineering & Technology
Dhaka - 1000, Bangladesh
Email: shourovcse@yahoo.com

***Abstract*—In this paper we have proposed a novel method to detect the defects in woven fabric based on the abrupt changes in the intensity of fabric image due to the defects and have constructed a classification model to properly identify the defects. We have also improved an existing method based on histogram processing for the classifier. In classification model we have implemented Artificial Neural Network (ANN). Both of our newly proposed method and improved technique have outperformed the existing methods. We have implemented K-validation to estimate the performance of our classification model. Additionally we have analyzed the performance of our classification model for different experimental parameters. Finally we have presented a comparative analysis of these techniques.**

***Index Terms*—K-Validation, Artificial Neural Network, Adaptive Median Filter, Roberts Operator**

I. Introduction

Countries like Bangladesh where textile merchandise is the major source of foreign income, an effective production flow and cost minimizing methods in textile industries are major requirements. As the main focus of the fabric industry is to export fabric material and finished goods, it is of utmost importance to detect and minimize faults in the fabric produced. Therefore efficient procedures should be applied in detecting the defects in fabrics. Compared to developed countries, defect detection in fabric in developing countries is still in primitive stage - it is manually done by human inspectors. This manual inspection system suffers from serious drawbacks which are concisely pointed out in [1] and [2]. In addition to these drawbacks there are various types of fabric defects that are caused by different factors as stated in [1] and [2] which are not discernible by human inspection. As a result the fabric exporters in developing countries have to compensate a considerable amount of money for fabric defects. For the past two decades a lot of research have been done to develop automated fabric defect detection systems based on computer vision as described in [1] and [2]. Some important aspects of developing an automated fabric defect detection system focusing the fabric industries of developing countries are environment of the industries, economic feasibility of the system, state-of-the-art technology etc. But the main focus of developing such system should be maximizing the accuracy while keeping the system economically feasible. Considering these aspects in this paper we first propose an improved approach similar to an existing automated defect detection method based on image histogram presented in [3] which is simple to implement and economically feasible. After that, we propose a novel approach where we use an edge detecting filter i.e. Roberts filter followed by simple morphology to identify the abrupt changes in the intensity of the image of fabric due to the presence of defects. This paper is organized is as follows. In Section II we discuss some notable research works regarding texture analysis and defect detection. In Section III we have described the preliminary concepts we have used in our study. In Section IV we have described our approaches and ideas. In Section V we have presented our experimental platform and the results we obtained from our experiment. We have also presented a comprehensive analysis of our experiment. We conclude in Section VI.

II. Literature Review

Different approaches have continually been applied in identifying fabric defects over the past decades. The analysis of texture image for detecting fabric defect is very intuitive. Implementing machine learning approaches for automated inspection system for textile industries is an imperative issue. In [4] the authors have proposed a method to detect both weave patterns and yarn color designs. An automated performance analyzer for fabric quality has been developed in [5]. Here image is prepossessed by Gaussian Filter and histogram equalization. Fourier transforms to recognize patterns in textile has been implemented in [6]. In this study the authors

[1]Contribution of all the authors in this paper are equal.

implemented the Fourier transform because of the periodic nature of patterns in textile. An adaptive wavelets has been applied into [7]. Adaptive wavelets can detect abrupt changes due to the defects in fabric. Another study regarding wavelet analysis is presented in [8]. Here 2-D image is converted into 1-D stream data. The authors have implemented feature extraction using wavelet transformation. In [9] authors use the Gaussian Markov random fields to construct a model of texture image. The inspection is regarded as statistical hypothesis based on the model. A combine image preprocessing and statistical techniques has been implemented in [10]. In this study image is preprocessed and model based clustering is implemented to capture an alignment pattern. Authors have proposed morphological filtering methods to segment the fabric image into background and defects in [11]. In their proposed schemes they have implemented a pre-trained Gabor Wavelet Network (GWN) for texture feature extraction of fabric. After that morphological processing is applied to isolate the defective portions. Our study also reviewed other machine learning approach combined with various image processing techniques.

III. Preliminaries

In this Section we present the general idea and concepts we use for development of our proposed approach. We present brief overview of the edge detection in spatial domain, the idea of image histogram, image restoration process, K-fold Validation technique.

A. *Edge Detection in Spatial Domain*

Edges are significant local changes of intensity of an image. They occur at the boundary between two different regions of an image. Edge detection [12] is particularly useful for feature extraction or feature detection for identifying areas in an image where discontinuities occur. Numerous Edge Detection Algorithms have been developed both in spatial and frequency domain. Edge detection filters in spatial domain [12] are based on derivative techniques. Some widely used Edge Detection filters are - Canny operator, Sobel operator, Roberts operator, Marr-Hildert operator etc. Among them Roberts Cross Gradient Operator is a simple and quickly computable 2-D spatial filter widely used for edge detection. It approximates the gradient by computing the partial derivatives which is achieved by computing the sum of the squares of the differences between diagonally adjacent pixels. It highlights regions of high spatial frequency which often correspond to edges. Roberts operator consists of a pair of $2X2$ convolution masks as shown in Figure 1.

B. *Image Histogram*

An image histogram is a graphical representation of the number of pixels in an image as a function of their intensity. By looking at the histogram the viewer can judge the intensity of pixel in the entire image. In case of a histogram of an 8-bit greyscale image the X-Axis represents the pixel intensity of the image ranging form 0 to 255 and Y-Axis represents the number of pixels on a particular grey level.

$$\underset{Gx}{\begin{array}{|c|c|}\hline +1 & 0 \\ \hline 0 & -1 \\ \hline \end{array}} \qquad \underset{Gy}{\begin{array}{|c|c|}\hline 0 & +1 \\ \hline -1 & 0 \\ \hline \end{array}}$$

Fig. 1. Roberts Cross-Gradient Operator

C. *Image Restoration Process*

Image restoration [12], like image enhancement is applied to improve an image prior to further operations. The main idea of image restoration process is to reconstruct or recover an image that has been degraded by using a prior knowledge of the degradation phenomenon/noise. The adaptive median filtering has been applied widely as an advanced method compared with standard median filtering for image restoration process. The Adaptive Median Filter performs spatial processing to determine which pixels in an image have been affected by impulse noise. The Adaptive Median Filter classifies pixels as noise by comparing each pixel in the image to its surrounding neighbor pixels. The size of the neighborhood is adjustable, as well as the threshold for the comparison. A pixel that is different from a majority of its neighbors, as well as being not structurally aligned with those pixels to which it is similar, is labeled as impulse noise. These noise pixels are then replaced by the median pixel value of the pixels in the neighborhood that have passed the noise labeling test.

D. *K-fold cross-validation*

Generally cross-validation is a technique for generating an assessment on how well a classifier will perform on the data it has not seen yet. Here the idea behind the concept is not to use the entire data set for training. Some training data has been removed and others are used to train the classifier. When the training of the classifier is complete, the data which has been removed can be used to test the performance of the classifier. The basic idea of evaluating a classification model is known as *cross validation*. In K-fold cross validation the whole dataset is divided into K equal sized separate subsets. Each time $K-1$ subset is used as training subset and the remaining subset is used as test subset. The advantage of this approach is that the division of data is not a major issue. Every data is used as training set exactly $K-1$ times and is used as test set only once.

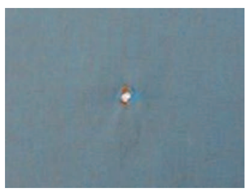
IV. Our Approach

In this Section we describe our approach to detect fabric faults. First we describe the steps that has been taken to acquire the images, then we describe our method regarding the edge detection principle, after that we describe our studies based on histogram processing. Later in the Section we describe how we design our classifier.

A. Image Processing and Extracting Feature Vector for ANN

a) Image Preprocessing - Image Acquisition and Restoration: In the proposed system, RGB image of fabric under inspection is captured using a high resolution digital camera. The inspection board is illuminated using three white lights placed 2 feet above the board. The camera is placed at the same height as the lights. A white background is placed under the fabric. This acquisition system is developed in accordance with the environment of fabric industries. Figure 2(a), 2(b) and 2(c) shows three RGB images captured with the proposed acquisition system. Then restoration process [12] is applied and RGB image is converted to grayscale image. The chosen restoration filter is the adaptive median filter [13] because of better noise removal ability and minimal time complexity compared to other filters.

(a) Image of Faultless Fabric



(b) Image of Fabric with Perforation

(c) Image of Fabric with Abrasion

Fig. 2. Original Image Captured by High Resolution Digital Camera

b) Image Segmentation and Feature Vector Preparation: We propose two simple and efficient segmentation techniques to prepare feature vectors or input dataset for Neural Network. In the next two sections we will focus our attention to these approaches.

B. Edge Detection Approach

The Edge Detection Method is based on the concept that, in the faultless portion of fabric image there are no discontinuities - sharp changes of pixels intensity. On the other hand there is an abrupt change in pixel intensity or presence of discontinuities in the portions with faults; the discontinuities occurring at the boundary between the faultless and faulty portions. As a result we can apply an edge detection algorithm on the fabric image and observe the differences between the faulty and faultless fabrics. Based on the above concept, we have proposed the following approach-

- As defects appear as irregular patterns on a uniform fabric, we implement a spatial mask for detecting edges in the image to approximate the defective portions. As defects are irregular in size, shape and pattern, we implement the spatial mask to detect edges in any direction. Our implemented spatial mask for edge detection is Roberts Cross Gradient Operator.
- Detection of edges in any direction sometimes results into very small sparse objects appearing in the image outside the Region Of Interest (ROI). We modify the image by removing these objects.
- Then we implement a simple morphological process [12] to separate the defects clearly. We use dilation [12] process and use "disk" as the structuring element.

This approach is simple in nature and have the benefits that are two folds. We do not have to use complex filters that require much computational resources and we can easily separate the faulty portion of the image from the faultless part. The formal representation of the algorithm is described in Algorithm 1.

Algorithm 1 Edge_Detection

input grayscale image I
I' = roberts_Operator(I)
if obejct area $<$ area_threshold **then**
  remove object
end if
I'' = dilate(I')
return binary image I''

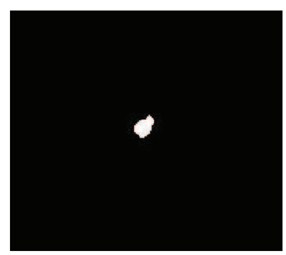
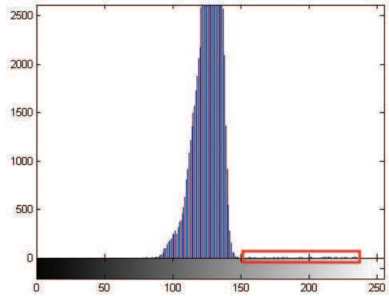


Fig. 3. Binary image of a perforated fabric when edge detection method applied

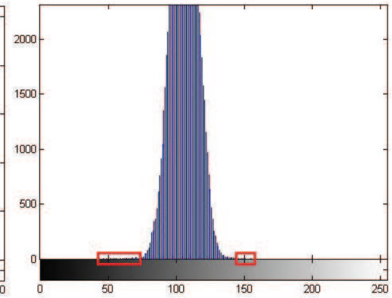
In Figure 3 binary image of figure 2(b) obtained using Algorithm 1 is shown. It can be seen that the proposed technique has identified the defected region (in this case perforation) properly. Another important fact is that edge detection relies on the detection of abrupt changes of pixel intensity on the fabric, so other kinds of defects such as burnout or discoloring can also be identified with this approach.

C. Histogram Processing

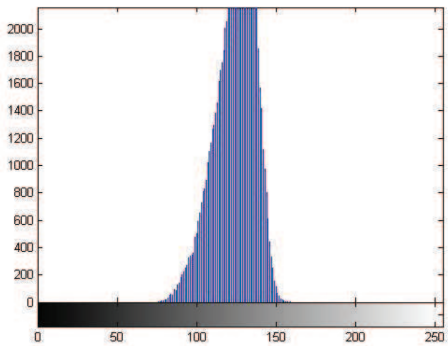
In [3] the authors have implemented an image segmentation technique which implements a decision tree model. A single threshold value is selected from fabric image histogram which is adjusted by the decision tree model. After carefully studying histogram processing techniques we observed histograms of more than 300 fabric images acquired using the acquisition system we developed and discussed in section IV-A. Based on our observation we have concluded that defects appear as



(a) Fabric Image with Perforation



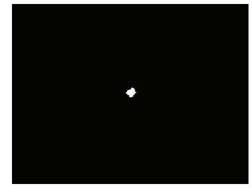
(b) Fabric Image with Abrasion



(c) Image of Faultless Fabric

Fig. 4. Histograms of Fabric Images

(a) Binary Image of Faultless Fabric



(b) Binary Image of Perforated Fabric

(c) Binary Image of Fabric with Abrasion

Fig. 5. Binary Images of fabrics after Segmentation using our Histogram Based Approach

small discontinuous portions in the histogram whereas uniform areas appear as a single dominant continuous portion from ascending to descending pixel numbers from lower to higher gray values. We also conclude that faults like perforations appear as small discontinuous portion mainly on the right side of the histogram and defects like abrasion appear mainly on the left side of the histogram with sometimes very small portion appearing on the right as well. Figure 4(a), 4(b) and 4(c) shows histograms of images with perforation(figure 2(b)), abrasion(figure 2(c)) and faultless image(figure 2(a)) with the defect portions highlighted. In the proposed algorithm we select two threshold values from image histogram and use them to segment the faulty portion (discontinuous parts in histogram) from the faultless portion (dominant continuous part in histogram). The general procedure is as follows:

- The first part of the algorithm selects $lower\_threshold$. We selected $pixel\_threshold\_one$ = 10 after rigorous experimentation.
- The second part selects $upper\_threshold$. $pixel\_threshold\_two = 15$ and C is an integer constant whose value is 10.
- The final part converts the grayscale image into a binary image using local thresholding technique [12] based on the two thresholds selected above.

Figure 5(a), 5(b) and 5(c) show the output binary images of input images of Figure 2(a), 2(b) and 2(c). The total procedure is described in Algorithm 2.

D. Feature Vector Preparation

After successfully processing the image by applying both of our proposed methods separately we acquire the following information from the binary image as feature vector to be used as input to the neural network.

1) Number of Objects in the binary image (objects denote defects)
2) Total Area of the Defective Portion
3) Total Perimeter of the Defective Portion
4) Circularity of the Defective Portion

E. Classification Model

We construct a three-layer feedforward neural network, which is trained by a dataset which consists of four features. The features described in Section IV-D are extracted from each image of training data set.

A three-layer feedforward neural network is typically composed of one input layer, one output layer and one hidden layer. In the input layer, each neuron corresponds to a feature; while in the output layer, each neuron corresponds to a predefined pattern. Classification process starts with training the neural network with a group of training samples. Every training sample belongs to a certain fabric defect. Then the testing samples are used to test the performance of the trained network. For an input feature vector the best output would be an output vector with all elements as zero, except the one, corresponding to which fabric defect the input sample belongs to. But, due to classification errors some sample input may not give the expected output. In our experiment, if any output neuron of network gives more than a threshold percent similarity, then that class of pattern is the potential match for input sample. If the input sample does not belongs to any class, then none of the output neuron would give more than threshold percent similarity as output [14].

In our proposed approach we use K-fold cross validation to perform classification on our data set. In K-fold cross validation dataset is divided into k equal sized subsets. Each

Algorithm 2 Histogram_Process

H = image histogram
for all $i = 0$ to $last(H)$ **do**
first_initial = first non_zero pixel gray value (x-value in histogram)
last = first gray value having pixel numbers(y-value in histogram) >= pixel_threshold_one
for all j = initial to last **do**
first_continuous = gray value from which pixel number is continuously increasing till last
if all y-values from initial to first_continuous are limited to zero and one **then**
lower_threshold = initial
break
else
lower_threshold = first_continuous;
break
end if
end for
break
end for
start_next = last + 50 (advance 50 x-values in the histogram);
for all i = start_next to last(H) **do**
second_initial = gray value having pixel numbers <= pixel_threshold_two
if there is a point between second_initial and second_initial + C with pixel numbers >= pixels_threshold_two **then**
replace second_initial with new gray value
end if
for all j = second_initial to last(H) **do**
if there is a gray value G with y-value = zero **then**
upper_threshold = G
break
end if
if between two adjacent gray values G_k and $G_{k+1}, y_k < y_{k+1}$ **then**
then upper_threshold = G_{k+1}
end if
end for
break
end for

time, one of the k subsets is considered as the test data set and the other $k-1$ subsets altogether form the training data set. The average error across all k trials is computed. Advantage of K-fold cross validation is to avoid the possible bias introduced by relying on any one particular division into test and train components. Our overall procedure is summarized in Figure 6.

V. Experimental Setup and Results

We have tested our approach on a computer with core-$i5$ processor and 4GB RAM using MATLAB 2009a. The

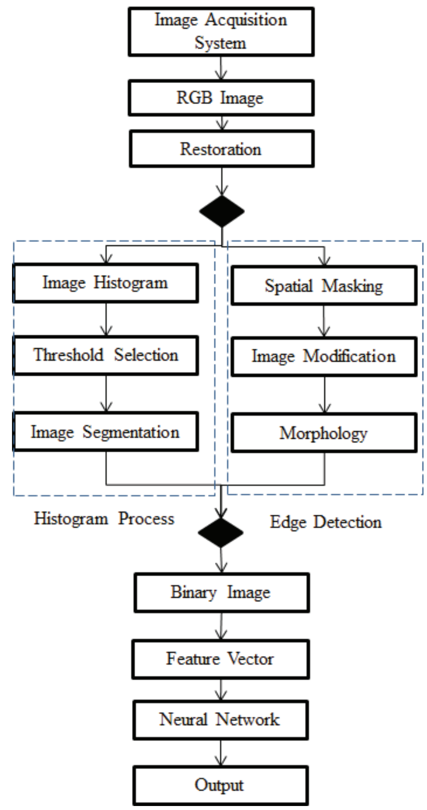


Fig. 6. Overview of the Overall Procedures of Our Approaches

resolution of image capturing device was 10 megapixels. We have conducted extensive experiment to estimate the practicability of our approach. We have performed experiments varying the number of neurons in the hidden layer and the number of iteration. Acceptable parameters have been found by keeping the number of hidden layer at 5, 10, 20, 25 and 30. We experimented with training iteration at 150, 200, 300, 350 and 400. Our complete source code has been uploaded on [15].

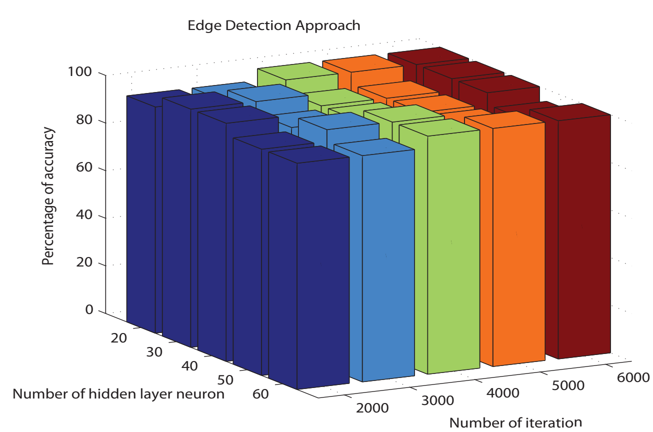


Fig. 7. Accuracy of Neural Network when feature extracted by edge detection method

As mentioned before we have proposed two methods for extracting feature vectors for training the Neural Network. We have reported the results of both of the methods. The accuracy percentage for both methods are shown in Figure 7 and 8. We can see from the figure that both methods have a very high accuracy and low error rate. From Figure 7 and 8 we can also conclude that the edge detection method outperforms the histogram processing method. It can be inferred from the figures that the features obtained from the edge detection method are well separated in the hyperspace. As a result decision obtained from the classifier have very high accuracy rate after being trained using K-fold validation technique.

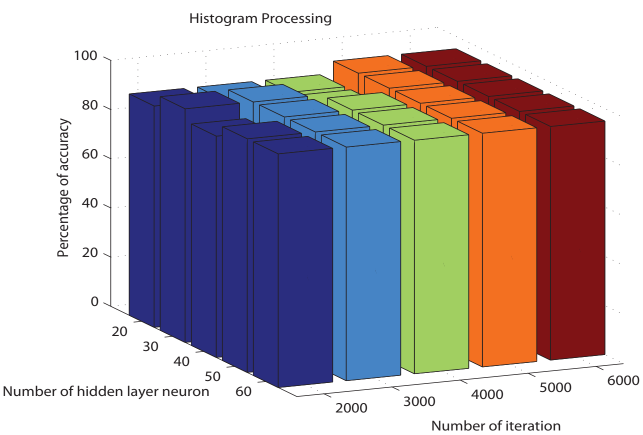


Fig. 8. Accuracy of Neural Network when feature extracted by histogram processing

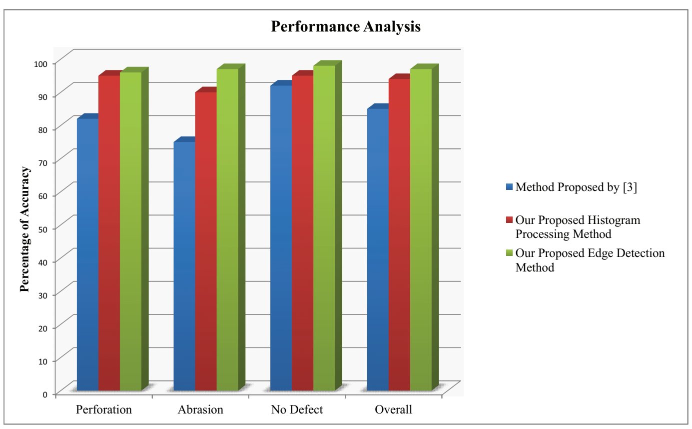


Fig. 9. Performance Analysis and Proof of Novelty of Our Methods

In Figure 9 we have shown the performance of our proposed two methods with the existing method proposed in [3]. From the figure it is evident that, both of our proposed methods have outperformed the existing method presented in [3]. Both of our proposed methods have individual defect detection accuracy rate of over 90% only in case of histogram processing method for abrasion the accuracy is just below 90%. It is also evident from the figure that, our proposed edge detection method has superiority over both the existing method in [3] and our improved histogram processing method which still has better accuracy rate compared to the method in [3]. In all cases overall accuracy of our proposed methods are over 90% where the edge detection method has better accuracy than histogram processing. Based on the above performance analysis we can conclude that our proposed histogram processing method is an improved and better method outperforming similar methods implemented in [3] and our proposed edge detection method is a novel approach outperforming both the existing methods and our proposed histogram processing method.

VI. Conclusion

In this paper we have investigated a novel approach to identify the defect of industrial fabric. We have presented two image processing techniques to extract the feature vectors to feed the ANN classifier. We have performed extensive experiments to find the suitable parameters for the classifier. We reported the results for both of our approaches and proved their novelty. Our motivation behind this research was to develop an efficient but cost effective automated fabric defect detection system for fabric industries of developing countries. Our methods are simple but very efficient and have been developed in accordance with the practical environment of the fabric industries of a developing country. We are interested in the further investigation to detect more complex and subtle defects which cannot be detected by human inspection.

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