

Fabric Defect Detection with Thresholding and Morphological based Segmentation Methods and Classification Using Neural Network

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Abstract—Defect in fabric causes loss for different textile companies whose aim is to produce quality fabric. Thus detection of faulty fabrics plays a core role in the improvements of any company. Now a days, the manufacture companies uses automated fabric defect detection methods under real time environment. These automated methods reduces the cost of labour and also improves economical conditions of companies. Automated system consists of robust as well as efficient fabric defect identification methods. In this paper we are presenting complete automated system which is based on the use of Thresholding Segmentation method for defect detection and Fuzzy Neural Network method for its classification. In implementation, we use Morphological operation based segmentation method, too and for the classification of different types of fabric defects, we are proposed to extract the features like geometric features as well as moment based features which are then stored in the neural network to have defect class as well.

The test results obtained exhibit accurate defect detection with low false alarms, thus showing the effectiveness and robustness of the proposed detection scheme.

Index Terms—Fabric Defect, geometric features, thresholding, segmentation, neural network.

I. INTRODUCTION

Defects are generated in woven fabric due to improper treatments in weaving machines, spinning errors and inadequate preparations of fiber at the spinning stage. In general, all defects alter the normal regular structure of fabric pattern and also modify the statistical and physical properties of the first quality fabric. The effects of defects are also dependent on the textural types of woven fabric.

The economic viability of a weaving plant is significantly influenced by the extent of its success in eliminating defects in fabric.

Fabric defect detection is a vital part of quality control

within the textile business. Usual strategies of fabric scrutiny on the assembly line is finished essentially by the employee on the circular knitting machine by introducing a lightweight supply within the middle of the circular product that allows the employee to observe the made defects, so stops the machine immediately. To increase accuracy, several specialists and researchers have presented lots of detection strategies supported automated visual systems, during which defect detection based on riffle rework has been a well-liked alternative for the extraction of textural options. For such industries it's needed to provide the simplest quality product throughout the short period of time. Within the garment industries, the various forms of cloth defects or faults square measure found around the troubles. So the manufacturer will earn solely 40-60 % for his or her benefit from such off quality product. So it becomes necessary to try and do the first detection of such cloth faults and recover them before golf stroke them into the market. The machine-controlled cloth defect detection is turning in to one among the fascinating analysis issues to researchers since from last decade and hence there square measure several strategies and techniques given by varied researchers. These strategies were given to beat the constraints of existing manufacturing method of materials. The material defect detection is turning in to one among the key elements in textile industries for internal control. To beat of these drawbacks this automation method are often enforced. As per our on top of discussion, the material defect identification is essential part of the standard management within the industries of textile.

Looking on the advances within the laptop resources, pattern recognition and image process, the FAVI system delivers the target, stable and reliable performance over the scrutiny of cloth defects. The simplest machine-controlled cloth defect detection technique is nothing however the one which may needs less labor value, less detection time and a lot of accuracy. FAVI system is best for human vision scrutiny.

Additionally to the current, texture has terribly high process complexness. The feel is nothing however the image patterns repetition that is perceived because then on directional or directional, rough or sleek, fine or coarse, regular or irregular etc. the material matter is largely consisting of pick and warp.

Moreover, massive irregularities in periodic structures of woven fabric (particularly for fabrics manufactured from natural fibers) introduce very high degree of noise, which make identification and classification of defects difficult. The problem is accentuated very much due to the hairiness of natural fibers.

II. LITERATURE SURVEY

In this section we are presenting review of previously presented different methods for fabric defect detection techniques.

In [2], Harlick has used the tone-texture concept to broadly classify the most commonly used texture analysis techniques into two categories: statistical and structural approaches. The pure structural models of image patterns are based on some primitives and placement rules.

Conci and Proença [3] have used the estimate of Fractal dimension (FD) on inspection images to detect fabric defects. In order to process large amount of image data, they have implemented the differential box counting method with the few modifications so as to minimize computational complexity and to enhance efficiency. The decision for defect declaration is based on the variation of FD.

Stojanovicet al. [4] have also developed a fabric inspection system that uses thresholding, noise removal followed by local averaging to identify eight categories of defects with 86.2% accuracy, however with 4.3% of false alarm.

Recently Tsai and Tsai [5] have proposed the use of color ring-projection algorithm for computational ease and demonstrated the defect detection which is invariant to the texture rotation.

In [6], Mallik-Goswami and Datta have also detected fabric defects using laser-based morphological operations. This approach filters out the periodic structure of fabric in the optical domain by inserting Fouries lens after proper spatial filtering. Thus the morphological operations are only performed on aperiodic images defects.

In [7], A. Serdaroglu presented the detection of fabric

defects using wavelet packet decomposition and independent component analysis has been investigated.

In [8], Kumar and Gupta have used mean and variance of wavelet coefficients for the identification of defects. The fabric defects can also be removed using wavelet shrinkage.

Since from literature survey, we have studied different methods for automated fabric defect detection and classification, but each method is associated with its disadvantages. In this paper we are introducing the new framework for fabric defect detections from real time fabric images and its classification using the thresholding and fuzzy neural network concepts. For accuracy we have used the preprocessing step as well. In next section II we are presenting the literature survey over the various methods of fabric defect detection. In section III, the proposed approach and its system block diagram is depicted. In section IV we are presenting the current state of implementation and results achieved and detailed description is given in section V. Results for both the methods are shown in section VI. Finally conclusion and future work is predicted in section VII. References are given in VIII.

III. PROPOSED APPROACH FRAMEWORK AND DESIGN

A. Problem Definition:

The fabric defects are to be detected and their classification according to the types is to be done for analysis of defects and their causes. So that we can directly discard the defected bunch of fabric to maintain the quality and to continue with production.

Here we are using Morphological operations based segmentation and thresholding based segmentation methods for the detection of flaws in the fabric and for classification, Neural Networks are being used. The comparative study is also to be given.

Architecture details:

The architecture is shown in figure. After capturing fabric image, it is first required to preprocess before going to the further detection.

We are using two classification methods to have good comparison as well. Each method extracts some required features to classify the defects in a specific class.

B. Proposed Architecture:

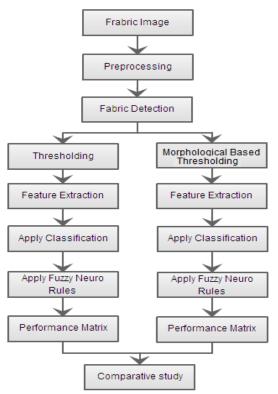


Fig. 1: Proposed System Architecture

IV. WORK DONE

A. Input:

For practical experiments, we use two-dimensional images of fabric.

B. Hardware and Software Configuration

Hardware Requirements:

Processor Ram	:	Pentium IV 2.6 GHz 512 MB DD RAM
Monitor Hard Disk	:	15" COLOR 20 GB
Software Requirem	ents:	20 00
Front End	:	Matlab
Tools Used	:	Matlab 2012
Operating System	:	Windows 7/8

V. DESCRIPTION OF EACH METHOD

A.Morphological operations based segmentation method:

The techniques of Morphological image processing are widely used for image analysis. Many successful machine vision algorithms used in character recognition, chromosome analysis and finger print classification are based on morphological image processing techniques. The morphological operations for defect detection in fabric are inherently sensitive to the size and shape of the defect. Therefore, while applying morphological image processing technique on the fabric image for the detection of defects, first a structuring element is required to be selected from the heuristic knowledge of the likely defects. Then secondly, the test image is thresholded and then morphological operations are applied on the thresholded image of the test fabric for the identification of defects.

A grayscale image can be considered as 3-D set where the first two elements are the x and y coordinates of a pixel and the third element is the gray-scale value. The structuring elements of the gray-scale morphological operations could have the same domains as those in binary morphology. However, a gray-scale structuring element is also possible having certain values instead of having only value 1 or 0.

Gray-scale opening and closing are defined in a similar manner as the binary case. The only difference is, when the operations are carried out, these opening and closing operations use gray-scale dilation and erosion. As binary morphological operations do, gray-scale opening is anti-extensive and gray-scale closing is extensive. Both operations make an original image smooth along to the nature of minimum and maximum functions.

A particular defect in the fabric image can be detected by eroding the image with a structuring element that is slightly smaller than the shape of the defect. For example, if the dimension of the structuring element is made slightly smaller than the average dimension of a knot, then the erosion operation of the fabric image with the structuring element will result in the complete elimination of the weft and warp structure of the fabric and only defect remains. The structuring element of a morphological operator is therefore a function defined in the domain of the spatial pattern. The value of each pixel of the domain is the weight or coefficient employed by the morphological operator at the pixel position. However, the selection of structuring element is not easy for the detection of thick yarn as the yarn may run through out the entire length of the fabric. The binary image is obtained from the gray level image by converting the pixel value to 1 (white pixel) if the value is greater than the preselected threshold value: otherwise the pixel value is returned to 0 (black pixel).

It is assumed that the threshold value does not depend on the spatial coordinates (i, j) and also threshold value is independent of local properties of the point. The warp defects can be detected with dilation and closing operations. The detection of missing weft by erosion and opening operations needs higher size structuring element. This is because of the continuity of the defective yarn throughout the length / breadth of the test fabric. Therefore, selection of structuring element is important factor which can be done satisfactorily by using rank order function.

Moreover, the rank order operator has unique property of image smoothing and presenting edges and at the same time it is very efficient for noise removal. In a woven fabric, repetition of the interlaced grating structure is not very accurate and therefore rank order operation proves to be an efficient tool for defect detection.

It may be noted that the rank-order operator is a generalization of the morphological erosion and dilation operations. Erosions and dilations are convolutions with maximum and minimum threshold value respectively. Therefore rank order operations require a structuring element as well. Rank order operator rotates in planar geometric structure, which is altered by probing with a structuring element called reference image. Each operation uses the reference image to determine the geometrical filtering process. The reference image or the structuring element of the operator is therefore a function defined in the domain of the spatial pattern of the operator.

The detection capability greatly improves by rank-order filtering which is termed as generalized morphological operations. Proper selection of the structuring element in all morphological operations enhances the chance of detection of defects.

The language of mathematical morphology is set theory. Sets in mathematical morphology represent objects in an image. In binary images, the sets in question are members of the 2-D integer space Z^2 where each element of a set is a 2-D vector whose coordinates are the (x, y) coordinates of a black or white pixel in the image.

Let A and B be sets in Z^2 . For binary images, defining the reflection of set B, denoted by

 $(A)_{z as} (A)_{z} = \{c | c = a + z, \text{ for } a \in A\}$

The four fundamental morphological operations are as follows:

The dilation of A by B: $A \oplus B = \{z | (B)_z \cap A \neq \emptyset'\}$ The erosion of A by B: $A \ominus B = \{z | (B)_z \subseteq A\}$ The opening of set A by structuring element B: $A \circ B = (A \ominus B) \oplus B$ The closing of set A by structuring element B: $A \bullet B = (A \oplus B) \ominus B$

These operations can be extended for grey-scale images. In particular, we are dealing with digital image functions of the forms f(x, y) and b(x, y), where f(x, y) is the input image and b(x, y) is a structuring element. If Z denotes

the set of real integers, the assumption is that (x, y) are integers from $Z \square Z$ and that f (x, y) and b(x, y) are functions that assigned a grey-level value to each distinct pair of coordinates. Denote Df and Db as the domains of f and b, respectively, the four fundamental morphological operations become:

Grey-scale dilation of f by b:

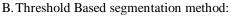
$$\begin{split} (f \oplus b)(s,t) &= \max\{f(s-x,t-y) + b(x,y)|(s-x), \\ (t-y) \in D_f; (x,y) \in D_b\}. \\ \text{Grey-scale erosion of f by b:} \\ (f \ominus b)(s,t) &= \min\{f(s+x,t+y) - b(x,y)|(s+x), \\ (t+y) \in D_f; (x,y) \in D_b\}. \\ \text{The opening of image f by structuring element b:} \\ f \circ b &= (f \ominus b) \oplus b. \\ \text{The closing of image f by structuring element b:} \\ f \bullet b &= (f \oplus b) \ominus b. \end{split}$$

The texture background of an image can be removed easily by the opening and closing operations. Also, the defect images left behind will be sharpened by the operations.

The last step of the proposed detection scheme is a thresholding step for producing a binary detection result. The thresholding limits λ_{max} and λ_{min} and satisfies the equation

$$\begin{cases} \lambda_{\max} = \max_{x, y \in \mathbf{W}} |C(x, y)| \\ \lambda_{\min} = \min_{x, y \in \mathbf{W}} |C(x, y)| \end{cases}$$

where C is the resulting fabric image obtained by applying a pair of opening and closing operations with the linear structuring element. It can also be seen that the proposed scheme can perform equally well in the case of bright defects with dark texture backgrounds, and in the case of dark defects with bright texture backgrounds. Even when the defect only alters the spatial arrangement of neighboring image pixels and not the mean grey level, the alteration can also be enhanced by the proposed scheme and the defect has been successfully segmented.



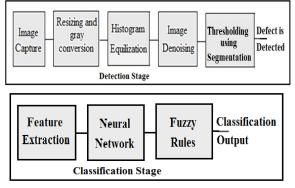


Fig: Block Diagram of system

The defects we have taken are Float, Knot, Hole, Gout, etc. for which the detection and classification are being done.

Fabric images are first captured with the help of camera. In our project, these images are taken from the dataset.

Pre-processing includes resizing, equalizing (contrast enhancing), noise removal process and segmentation of image for thresholding then feature extraction.

The Histogram Equalization does contrasting to performs uniform distribution of gray pixels in the image.

Noise is random variation in the intensity or brightness in an image which can be eliminated by using Adaptive Wiener Filter that considers local neighborhood of each pixel and therefore maintains sharpness while de-noising.

The image segmentation is nothing but partitioning the image into multiple segments. Each pixel in the image has same characteristics. The defected pixels then can easily be differentiated by segmentation.

Thresholding divides the pixels in foreground and background segments where defect can be highlighted. It is but intensity based histogram of an image.

Transforming the input data into the set of features is called Feature Extraction. Feature provides the useful information and reject the rest.

Types- Geometric features, Intensity features, etc.

Gray level based features are extracted using GLCM method which includes 'contrast', 'correlation', 'energy', 'Homogeneity'.

Contrast: The intensity contrast between a pixel and its neighbor over the whole image.

Range = $[0 (size(GLCM, 1)-1)^2]$. Contrast is 0 for a constant image.

$$\sum_{i,j}|i-j|^2\mathsf{p}(\mathsf{i},\mathsf{j})$$

Correlation: Is a statistical measure of how correlated a pixel is to its neighbor over the whole image.

Range = [-1 1] Correlation is 1 or -1 for a perfectly positively or negatively correlated image.

$$\sum_{i,j} \frac{(i-\mu i)(j-\mu\,j)p(i,j)}{\sigma_i \sigma_j}$$

Energy: Is a summation of squared elements in the GLCM. Range = [0 1]. Energy is 1 for a constant image.

$$\sum_{i,j} p(i,j)^2$$

Homogeneity: Is a closeness of the distribution of elements in the GLCM to the GLCM diagonal.

Range = [0 1]. Homogeneity is 1 for a diagonal GLCM.

$$\sum_{i,j} \frac{p(i,j)}{1+|i-j|}$$

Intensity based feature extraction computes area and perimeter of an segmented image.

The Eccentricity is the ratio of the distance between the foci of the ellipse and its major axis length. Eccentricity and Average Intensity is then computed and the Average Mean of all the features are then taken to train the set for classification.

The classification system is divided into two Phases:

Training Phase: The NN has to be trained with the data set images for different defects and the defect free images too.

Testing Phase: The input image is verified for existence of fault and its type.

NN is first used to classify the defect type and for more accuracy the Fuzzy rules are being used to fix the specific defect type for an input image.

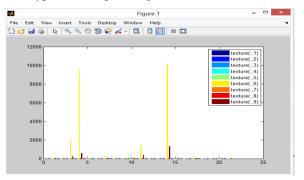
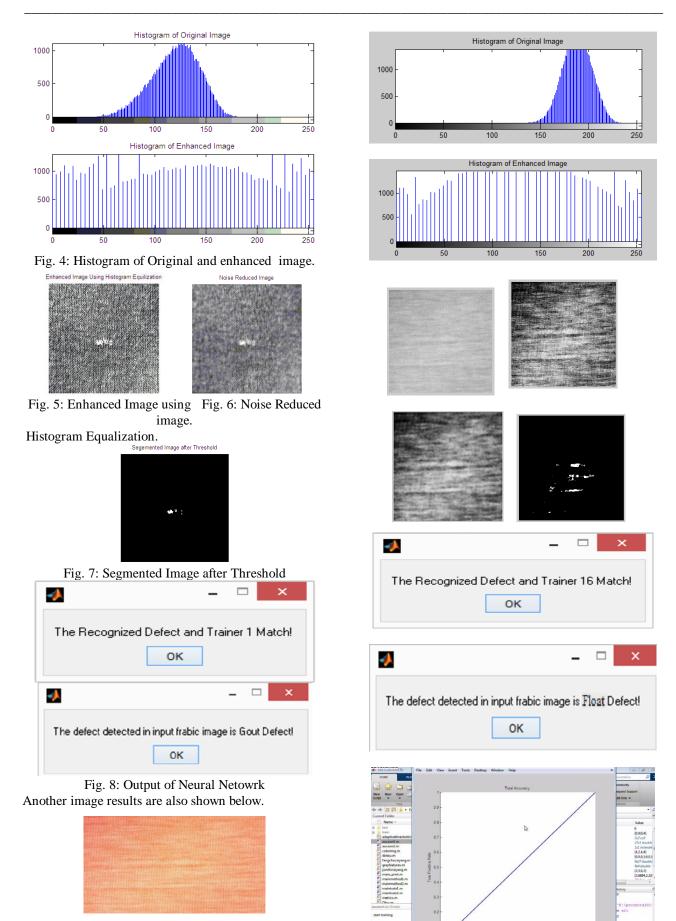


Fig: Feature graphs for all 9 features

IV. RESULTS OBTAINED BY THRESHOLD BASED SEGMENTATION METHOD



Fig. 2: Input Image of fabric Fig. 3: Preprocessed image.



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Fig: Graph for accuracy for Thresholding method

> aucann1				
Name	Size	Bytes	Class	Attributes
labels	27x1	216	double	
texture	27x9	1944	double	
In <u>confusi</u> In <u>aucann</u> Percentage C	on at 46	fication :	96.440000)\$
In <u>confusi</u> In <u>aucann</u> Percentage C Percentage I	on at 46 at 20 Correct Classif Incorrect Class	fication :	96.440000	
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In <u>confusi</u> In <u>aucann</u> Percentage D Percentage I Marning: Tar In <u>confusi</u> In <u>plotcon</u>	on at 46 at 20 Forrect Classif Incorrect Class gets were not on at 46	fication : sification : all 1/0 valu	96.440000	18

Fig: Performance window for Threshold method

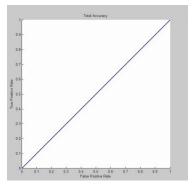


Fig: Graph for accuracy for Morphological method

	Hidden Layer 3	Output Layer Output Layer Couport 2	
Algorithms	8 8	1	
Data Division: Random	(dividerand)		
Training: RProp (tr	rainrp)		
Performance: Mean Squ			
Derivative: Default (defaultderiv)		
Progress			
Epoch: 0	7 iterations	1000	
Time:	0:00:00		
Performance: 4.37	1.10	0.00	
Gradient: 10.3	3.40	1.00e-05	
Validation Checks: 0	6	6	
Plots			
Performance (plo	tperform)		
Penoimance (pio	and a straight of the		
	ettrainstate)		
Training State (plo	vtrainstate) vtregression)		

Fig: Neural Network result for Morphological method

>> aucann2				
Name	Size	Bytes	Class	Attributes
labels	27 x1	216	double	
texture	27x9	1944	double	
Percentage In	at 20 prrect Classif ncorrect Class	ification :	0.000000	
> In confusio	on at 46			
In plotcont	fusion>update	plot at 399		
In plotcont	fusion at 108			
In aucann2	of 25			

Fig: Performance window for Morphological method

VI. CONCLUSION AND FUTURE WORK

In this paper we have presented the new approach for automated fabric defect detection using the thresholding and morphological operations based segmentation method and classification Neural Network is used with the help of fuzzy rules logic. There are different kinds of fabric faults or defects, however in literature we have not addressed any single method to classify or identify them differently as well as required level of accuracy. Instead comparison is also done and to include to have good study. The comparison is performed under two factors accuracy and detection time. The performance of proposed approach is showing better performance as compared to the existing methods. Even second method shows exact results with no false alarm. For the future work we suggest to work on automated system to deploy in fabric industries successfully.

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