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Fabric Fault Detection using Local Derivative Pattern and Gabor Filter Approach

B. G. Chhapkhanewala, S. L. Vaikole

***Abstract:** The aim of this is to design a defect detection system using image processing techniques. Inspection process is very important for textile industry. Defects decrease the profits of manufacturers and cause undesirable loses. Therefore, to reduce loses manufactures initially started to employ experts to detect the currently available defects on the fabrics. An effective defect detection scheme for textile fabrics is designed in this article. Interestingly, this approach is particularly useful for patterned fabric. In the proposed method, firstly, Local Derivative Pattern (LDP) is adjusted to match with the texture information of non-defective fabric image via genetic algorithm. Secondly, adjusted optimal Gabor filter is used for detecting defects on defective fabric images and to be detected have the same texture background with corresponding defect-free fabric images. Gabor filter is adjusted to match with the texture information of non-defective fabric image via genetic algorithm. The novel high-order local pattern descriptor, local derivative patterns (LDP), for face recognition. LDP is to encode directional pattern features based on local derivative variations. The (n)th-order LDP is proposed to encode the (n-1)th-orders local derivative direction variations, which can be more detailed information than the first-order local pattern used in local binary patterns (LBP).*

***Index Terms:** Fabric Fault Detection, Gabor filter, Local Derivative Pattern (LDP), Support Vector Machines (SVM) classier.*

I. INTRODUCTION

Nowadays, with the rapid development of computer and image processing technology, computers vision has been widely used in textile industrial production. Therefore, automated fabric defect detection becomes a natural way to improve fabrics quality and reduce labor costs [1]. Since 1980s, many researches in the field of fabric defect detection based on computer vision have been widely carried out. In practical application field, defect inspection equipment's included Usters Fabriscan, IQ TEX-4, Barcos Vision Cyclops and German mahlo WEBSCAN WIS-12 [2], but the cost of investments is higher and the enterprise recovery time is longer. Thus, the development of automated fabric defect detection with high accuracy and fast speed seems to be necessary and has profound significance [3].

Fabrics are the raw materials of textile industry and they have very sensitive structure. Consequently, quality is very important parameter for textile, so good qualities products is a key issue for increasing rate of profit and customer satisfaction. Around seven cover billion people are currently live on in the world and all the people use clothes to their bodies. Therefore, textile industry becomes very large and an important sector.

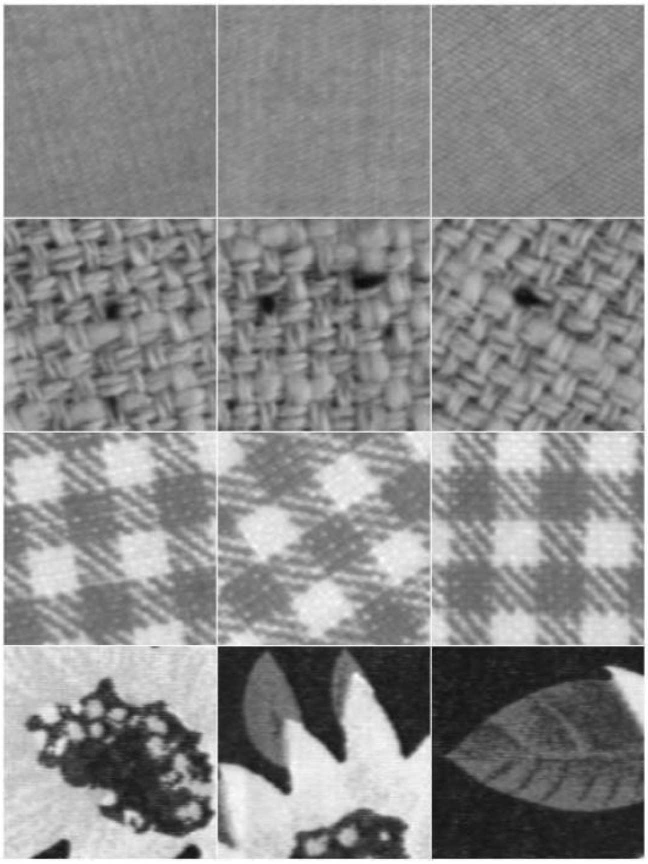

Figure 1: Examples for the Four Classes Included in the Reference Dataset Each Picture Line Shows Three Representatives of a Class.

Textile industry is one of the main sources of revenue-generated industries. Fabric defect detection, as a popular topic in automation, is a necessary and essential step of quality control in the textile manufacturing industry. A very small percentage of defects are detected by the manual inspection even with highly trained inspectors which is time consuming and not accurate enough. An automatic defect detection system can increase the defect-detection percentage; it reduces the fabrication cost and economically profitable when we consider the labor cost and associated benefits. An effective defect detection scheme for textile fabrics is designed in this paper. The proposed method, firstly, Local Derivative Pattern (LDP) is adjusted to match with the texture information of non-defective fabric image via genetic algorithm. Secondly,

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***Correspondence Author(s)**
Burhanuddin GulamAbbas Chhapkhanewala, Department of Computer Engineering, Datta Meghe College of Engineering, Airoli (Maharashtra), India. E-mail: burhanroyal@gmail.com
Dr. S. L. Vaikole, Associate Professor, Department of Computer Engineering, Datta Meghe College of Engineering, Airoli (Maharashtra), India. E-mail: slv.cm.dmce@gmail.com

Adjusted optimal Gabor filter is used for detecting defects on defective fabric images and defective-fabric image to be detected have the same texture background with corresponding defect-free fabric images [4].

II. REVIEW OF LITERATURE

Traditionally, this fabric fault detection was performed by well-trained human inspectors [1]. When the inspector notices a defect on the moving fabric, he stops the machine, records the defect and its location, and starts the motor again. Therefore, automatic inspection systems were introduced to achieve 100% accuracy [5]. Unfortunately, most of the used algorithms are computationally complex for on-line applications, where they classified the algorithm into four categories. They are:

- Structural Approaches,
- Statistical Approaches,
- Spectral Approaches, and
- Model Based Approaches.

2.1 Structural Approaches Use Primitives.

These primitive can be as simple as single pixels. Consequently, the main objective of these approaches is firstly to get these primitives, and secondly to generalize the spatial placement rules. However, these approaches were not successful on fabric defect detection, mainly due to noise, etc.

2.1.1Kumar A., introduces Computer vision-based fabric defect detection: a survey

Categorization of fabric defect detection techniques is useful in evaluating the qualities of identified features. The characterization of real fabric surfaces using their structure and primitive set has not yet been successful. Therefore, on the basis of the nature of features from the fabric surfaces, the proposed approaches have been characterized into three categories; statistical, spectral and model based. In order to evaluate the state-of-the-art, the limitations of several promising techniques are identi_ed and performances are analyzed in the context of their demonstrated results and intended application.

2.2 Statistical Approaches

Measure the spatial distribution of pixel values while their main objective is to separate the image of the inspected fabric into the regions of distinct statistical behavior [6].

- Co-occurrence matrix
- Histogram methods
- Auto-correlation function

2.2.1 *Mahajan P.M., Kolhe S.R. and Patil P.M.,* introduces *A review of automatic fabric defect detection techniques*

An optimal solution for this would be to automatically inspect from the fabric as it is being produced and to alert the maintenance personnel when the machine needs attention to prevent production of defects or to change process parameters to prevents automatically to improve product quality. This is done by identifying the faults in fabric using the image processing techniques and then based on the dimension of the faults; the fabric is classified and then graded accordingly.

Strengths

- Extracting spatial relationship of pixels with different 14 statistical computations
- High accuracy rate
- Computational simplicity.
- Invariant to translation and rotation
- Ideal for use in application to tonality discrimination

Weaknesses

- Computationally expensive for the demands of a real-time defect inspection system.
- Difficult to determine the optimal displacement vector
- Require feature selection procedure
- Dependent on the rotation and scaling
- Sensitive to noise
- Low detection rate in the error-detection of non-regular textures

2.3 Spectral Approaches

This approaches are less sensitive to noise and intensity variations than other approaches. The primary objectives of this approach are to get the primitives, and to model or generalize the spatial placement rules.

- Wavelet transform
- Fourier transform
- Gabor transform

2.3.1Y. Ben Salem, S. Nasri, introduces *Woven Fabric Defects Detection based on Texture classification Algorithm*

In this, they use the multi-class support vector machine as a classifier. The main aim of such classifier is to obtain a function f(x), which determines the decision boundary or the hyper-plane. This hyper-plane optimally separates two classes of input data points. The margin M is the distance from the hyper-plane to the closest point for both classes of data points [7].

Strengths

- Provides multi-scale image analysis
- Enables to identify different defect types with different mother wavelets
- Textural feature extraction and possibility of direct thresholding
- It can be used for noise reduction
- Provides a high accuracy rate
- Efficiently compresses the image with little loss of information
- Utilization in weaving and knitting machines to detect and identify defects

Weaknesses

- In adaptive use, high computational cost
- It suffers from either image components interference or features correlations between the scales

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2.3.2Junfeng Jing, Panpan Yang, Pengfei Li and Xuejuan Kang, introduces *Supervised defect detection on textile fabrics via optimal Gabor filter*

1. Firstly, Gabor filter is adjusted to match with the texture information of non-defective fabric image via genetic algorithm.
2. Secondly, adjusted optimal Gabor filter is used for detecting defects on defective fabric images and to be detected have the same texture background with corresponding defect-free fabric images.

Strengths

- Offers optimal defect detection for both spatial and frequency domain
- An adaptive filter selection method is implemented to reduce the computational complexity
- Utilization in weaving and knitting machines to detect and identify defects

Weaknesses

- The choice of optimal filter parameters is quite difficult
- It is not invariant to rotation Intensive computation

2.4 Model-Based Approaches

In this analysis method model the texture by finding the parameters of predefined model. This task is difficult if a large number of models must be considered. From our survey, it is concluded that the need for a consistent way to produce defect-free fabrics.

2.5 Summary

In this chapter a review on some notable and recent research work done on Automatic Fabric Defect Detection. Presenting all proposed methods on these methods is beyond a scope. Most existing multi-label learning methods exploit the label correlation only in the output label space, leaving the connection between label and features of images untouched. And some methods exploiting the label correlation in the input feature space by using the label information; they cannot effectively conduct the learning process in both spaces simultaneously, and there still exists much room for improvement.

(a)

(b)

Figure 2: Shows the types of inspections (a) Manual and (b) Machine Automated

The goal is to do classification of input image with the existing textures template. Texture segmentation is achieved using texture properties. Fig. 1 (a) and (b) shows the types of fabric defect inspections.

III. CHALLENGES

3.1 Investigation of Raw Materials:

A fabric defect can occur right from raw material selection to finishing stage, because of improper input parameters with respect to material, machine and man. Any variation to the knitting process needs to be investigated and corrected [11].

3.2 Fault Detection Time:

Defects fall into the category. Since when they appear, repair is needed, this is time consuming and sometimes results in fabric rejection. Fabrics defect detection has been a long felt need in the textile and apparel industry. Surveys carried out in the early 1975 shows that inadequate or inaccurate inspection of fabrics has led to fabric defects being missed out, which in turn had great effects on the quality and subsequent costs of the fabric finishing and garment manufacturing processes.

3.3 Algorithm Complexity:

Digital image processing is the use of computer algorithms to perform image processing on digital images. As a subcategory or field of digital signal processing, digital image processing has many advantages over analog image processing. It allows a much wider range of algorithms to be applied to the input data and can avoid problems such as the build-up of noise and signal distortion during processing [1].

3.4 Image Extraction:

Image processing is a method to convert an image into digital form and perform some operations on it, in order to get an enhanced image or to extract some useful information from it [7]. It is a type of signal dispensation in which input is image, like video frame or photograph and output may be image or characteristics associated with that image [8].

IV. METHODOLOGY

In this section, the method is described. Fabric defect detection processing consists of three parts: a) calibration, b) defect image inspection and c) threshold comparison. Calibration is mainly to prepare for obtaining the relevant parameters which are used to reduce noise of defect images in defect detection. Image features are extracted by LDP, and then the filtered images are divided into a large number of non-overlapping sub-blocks. Afterwards, the data fusion of the corresponding sub- blocks divided from fabric images and the high-dimension data of fused sub-blocks feature vectors are reduced by Gabor filters,and then the median filtering and similarity comparison are operated on the low-dimension feature vectors. Finally, the SVM classifier is used to classify the defected image from the defect free image.

4.1 Image Acquisition

In this step, the image file is read and converts into an array of bitmaps. This includes interpretation of the image format (like jpeg, png, etc). We have chosen to work with TILDA database, elaborated by the Technische University Hamburg in 1995, which consists in 4 different textiles. These are various ways are provided to capture image. Some are described as two dimensional-CCD, line scan camera where element is arranged in one-dimensional CCD. While approaching 2-D system, some issues as blurring, inspection speed, restriction of inspection range.

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This issue can be overcome with the help of fast camera acquisition, 7k pixels or above resolution to be used.

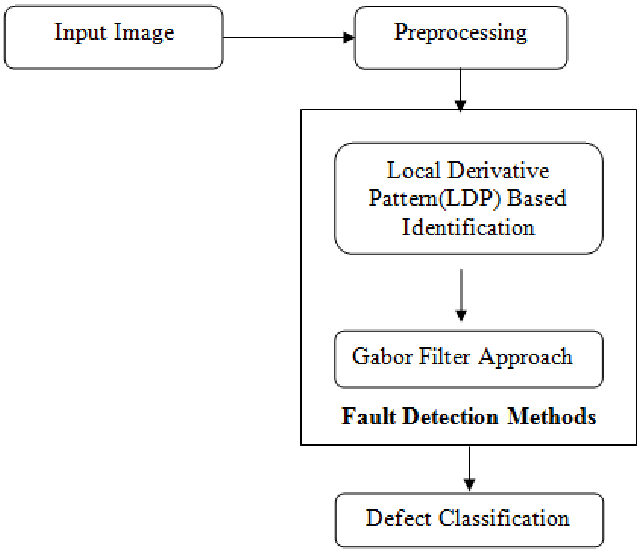

Figure 3: Flowchart of Proposed Methodology

4.2 Data Pre-Processing

The acquired image cannot be directly used for detection as it will have some unwanted factors which hamper the fault detection accuracy. The aim of preprocessing is to reduce these factors. We use contrast stretching and noise filtering techniques in this stage.

This gives rise to two advantages in image quality improvement: enhancement to a large extent of the contrast of the image and effective elimination of the uneven background illumination caused during image taking. For the normalization of feature values, Softmax normalization is used. Various ways are provided to capture image. Some are described as two-dimensional CCD, line scan camera where elements is arranged in 1-dimensional CCD. While approaching 2-D system, some issues as blurring, inspection speed, restriction of inspection range. This can be overcome with the help of fast camera acquisition, 7000 pixels or above resolution to be used. But since these cameras are costing too much, so inspection algorithm can be approached.

Preprocessing of the data is a necessity which includes image denoising, image enhancement, normalization of feature values, etc. For the pre-processing of images, we choose the technique of block histogram equalization which, instead of implementing equalization on the whole 256*256 pixels image, implements equalization on each of the 32*32 pixels sub-images.

4.3 Thresholding

The acquired image is generally color or gray-scale image. However, for feature detection algorithm (next step) we need binary images. Thresholding is used to convert gray-scale images to binary images. Selecting the correct thresholding value is important at this stage.

LBP is defined as a gray-scale invariant texture measure and is a useful tool to model texture images. The original LBP operator labels the pixels of an image by thresholding the 3x3 neighborhood of each pixel with the value of the central pixel and concatenating the results binomially to form a number.

4.4 Feature Extraction

The thresholded image now will contain only the significant features of the image, which maybe a fault. At this stage we identify and isolate all the major features in the image, like big blobs or objects with bounded area.

With the help of data preprocessing, the obtained image will be checked for extracted pattern and compared with library or last posted images. This can be done with LDP algorithm.

4.4.1Local Derivative Pattern

The local binary pattern (LBP) features are originally designed for texture description. The operator has been successfully applied to facial expression analysis, background modeling and face recognition. The LBP feature is that a face can be seen as a composition of micro-patterns [9]. LBP in nature represents the first-order circular derivative pattern of images, a micro-pattern generated by the concatenation of the binary gradient directions. However, the first-order pattern fails to extract more detailed information contained in the input object. LBP is defined as a gray-scale invariant texture measure and is a useful tool to model texture images. The original LBP operator labels the pixels of an image by thresholding the 3x3 neighborhood of each pixel with the value of the central pixel and concatenating the results binomially to form a number.

$$f(I(Z_0),I(Z_i)) = \begin{cases} 0, & if\ I(Z_i)-I(Z_0) \le threshold \\ 1, & if\ I(Z_i)-I(Z_0) > threshold \end{cases}, i = 1,2,...,8 \qquad (1)$$

LBP actually encodes the binary result of the first-order derivative among local neighbors by using a simple threshold function as shown in (1), which is incapable of describing more detailed information.

Z_1	Z_2	Z_3
Z_8	Z_0	Z_4
Z_7	Z_6	Z_5

Figure 4: Example of 8-Neighborhood Around Z_0

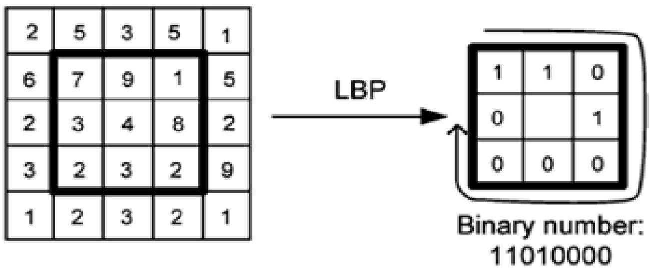

Figure 5: Example of Obtaining the LBP Micro-Pattern for the Region in the Black Square.

An LDP operator is proposed, in which the (n-1)th-order derivative direction variations based on a binary coding function. In this, LBP is conceptually regarded as the non-directional first-order local pattern operator; because LBP encodes all-direction first-order.

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Derivative binary result while LDP encodes the higher-order derivative information which contains more detailed discriminative features that the first-order local pattern (LBP) cannot obtain from an image.

Given an image I(Z), the first-order derivatives along 0 , 45 , 90 and 135 directions are denoted as $I_1(Z)$ where a = 0, 45 , 90 and 135 . Let Z_0 be a point in I(Z), and Zi, i=1,....,8 be the neighboring point around Z_0. The four first-order derivatives at Z= Z_0 can be written as

$$I'_{0^0}(Z_0) = I(Z_0) - I(Z_4) \qquad (2)$$

$$I'_{45^0}(Z_0) = I(Z_0) - I(Z_3) \qquad (3)$$

$$I'_{90^0}(Z_0) = I(Z_0) - I(Z_2) \qquad (4)$$

$$I'_{135^0}(Z_0) = I(Z_0) - I(Z_1) \qquad (5)$$

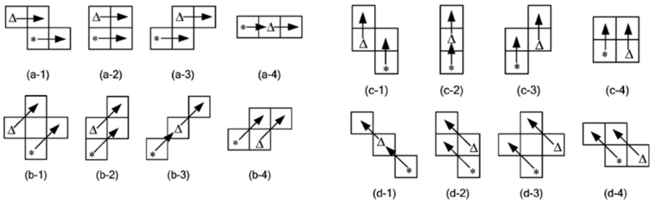

Figure 6: Illustration of LDP Templates.

In this way we can extract the feature and then we are giving this feature to Gabor filter to extract more feature because in LDP we can only extract the pattern base feature but if the pattern various then for that only LBP not sufficient so we are giving to Gabor filter.

4.4.2Gabor filter

In this approach, A two-dimensional (2-D) Gabor function is a complex exponential function assigned by the given sinusoidal wave frequency u0 and rotated orientation θ. Meanwhile, Gabor function is modulated by 2-D Gaussian function which involves three parameters in spatial domain.

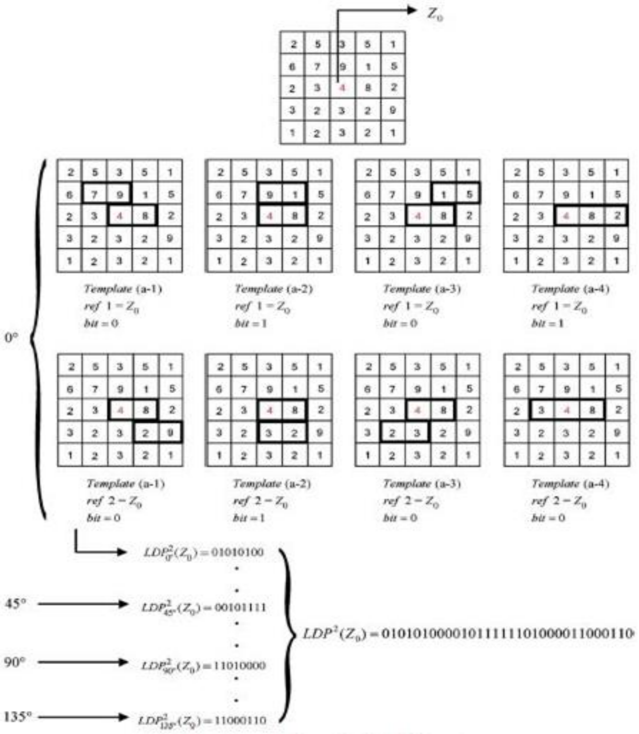

Figure 7: Example to Obtain the Second-Order LDP Micro-Patterns.

The parameters are expressed as (σ. x; σ. y) and orientation θ which rotates the values x and y to the corresponding x^1 and y^1, and they have variances along the x-axis and y-axis, respectively. Objective response of Gabor function in the 2-D space domain can be defined as follows:

$$g(x,y) = \frac{1}{2\pi\sigma_x\sigma_y} exp\left\{-\frac{1}{2}\left[\left(\frac{x'}{\sigma_x}\right)^2 + \left(\frac{y'}{\sigma_y}\right)^2\right]\right\} exp\,(j2\pi\mu_0 x') \qquad (6)$$

The real part of 2-D Gabor function shown as equation (8) acts as an even symmetric Gabor filter to detect fabric blob section. While, the imaginary part of 2-D Gabor function indicated as equation (9) is used for detecting fabric edge part as an odd symmetric filter. The relationship of two portions and integrated Gabor filter can be described as in equation (7).

$$g(x,y) = g_e(x,y) + jg_0(x,y) \qquad (7)$$

$$g_e(x,y) exp\left\{-\frac{1}{2}\left[\left(\frac{x'}{\sigma_x}\right)^2 + \left(\frac{y'}{\sigma_y}\right)^2\right]\right\} cos(2\pi\mu_0 x') \qquad (8)$$

$$g_0(x,y) = exp\left\{-\frac{1}{2}\left[\left(\frac{x'}{\sigma_x}\right)^2 + \left(\frac{y'}{\sigma_y}\right)^2\right]\right\} sin(2\pi\mu_0 x') \qquad (9)$$

4.5 Support Vector Machines (SVM) classifier

A SVM works by building a hyper-plane or set of hyper-planes in a high dimensional space, used for classification. If the hyper-plane has the largest distance to the nearest training data point of any class then good separation is achieved. Generally larger the margin lower will be the generalization error of classifier [10].

SVM uses non parametric approach and binary classifiers. Performance of SVM is dependent upon the hyper-plane selection and kernel parameter.

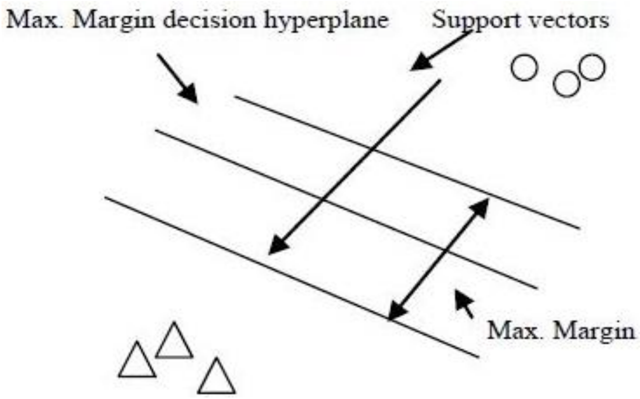

Figure 8: Showing Maximum Margin between Two Hyper-Planes Separating Two Classes

4.5.1 Binary Classification

Given training data (xi, yi) for i = 1 ...N, with xi Rd and yi 1, 1, learn a classifier f(x) such that

$$f(x_i)\begin{cases} \geq 0, & y_i = +1 \\ < 0, & y_i = -1 \end{cases} \qquad (10)$$

i.e. $y_i f(x_i) > 0$ for a correct classification.

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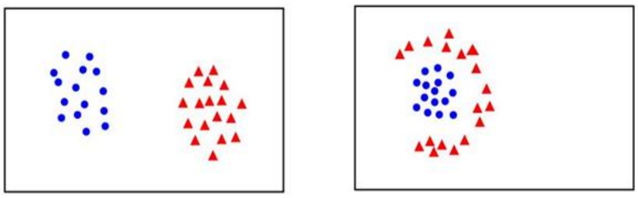


Figure 9: Binary Classification

4.5.2Linear Classifiers

A linear classifier has the form $f(x) = w^T x + b$.

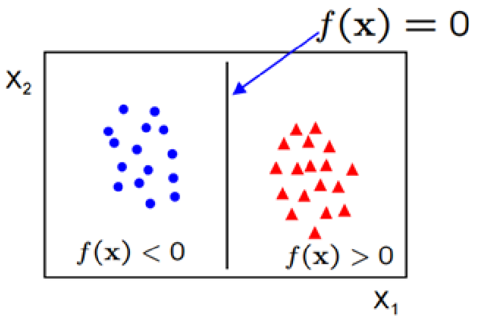
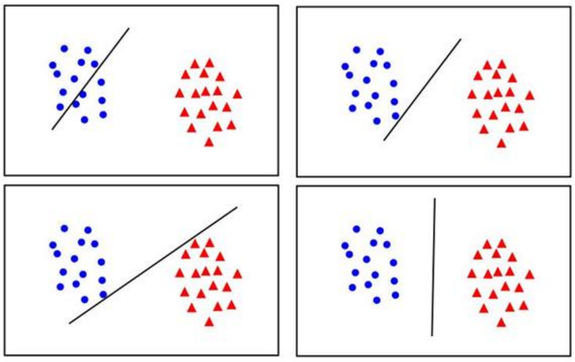


Figure 10: Linear Classifiers

In Figure 10, Where, in 2D the discriminant is a line is the normal to the line, and b the bias is known as the weight vector.

What is the best w?



4.5.3Support Vector Machine

Since $w^T x + b = 0$ and $c(w^T x + b) = 0$ define the same plane, we have the freedom to choose the normalization of w.

Choose normalization such that $wTx + + b = +1$ and $wTx - + b = -1$ for the positive and negative support vectors respectively.

Then the margin is given by

$$\frac{w}{\|w\|} \cdot (x_+ - x_-) = \frac{w^T (x_+ - x_-)}{\|w\|} = \frac{2}{\|w\|}$$

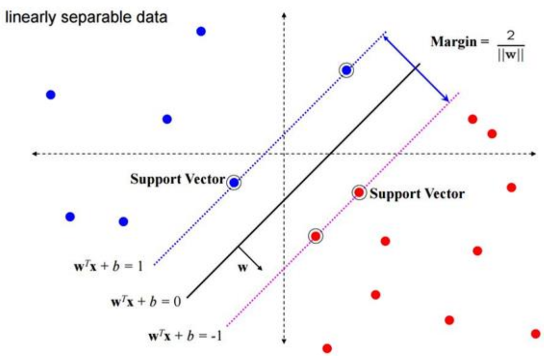


Figure 12: Support Vector Machine

4.6 Recognition

In this research we consider the different patterns of fabric images like box type, dot type and star type. These patterns are mainly occurred with six different types of defect likes broken needle, hole, netting multiple, thick bar, thin bar and Barrie [14]. Example of the defected fabric samples are shown in fig. 13

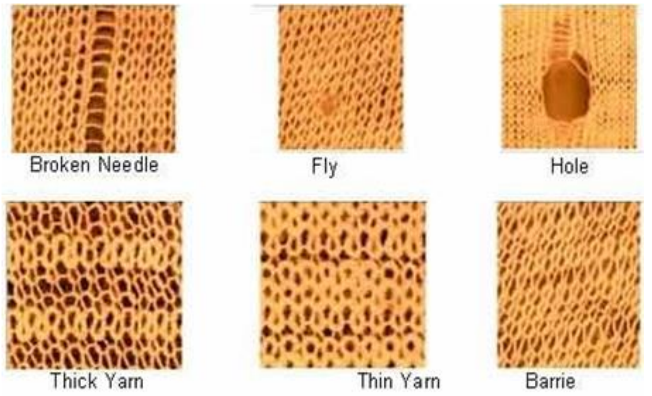


Figure 13: Support Vector Machine

From previous, we recognize whether a particular shape indicates a fault. This is done mainly by comparing the relative size and number of features. Images with faulty fabric tend to have few big features whereas non-fault images tend to have many small features. We use this data to recognize whether the image is of a faulty fabric.

V. EXPERIMENTAL RESULTS & PERFORMANCE ANALYSIS

5.1 Experimental Result

In this system, the non-defected image is given first to the system to recognize the pattern of fiber. In the given experimental result, As shown below.

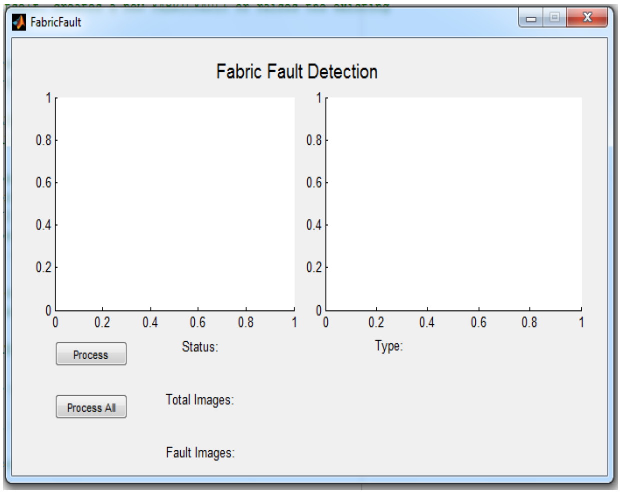


Figure 14: Result GUI

In the Second image Fig 15 the image is selected to check the defect in the image or not. There is a small defect is detect by the proposed system. In the image, there is some thread knot present. This may affect the fabric cost.

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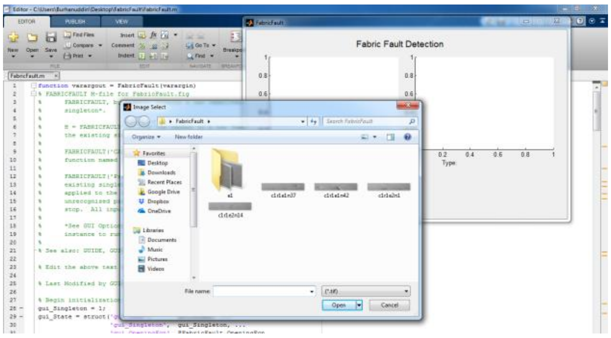

Figure 15: Selecting Image

So the system is first converting that into gray-scale and enhances the image. Then by applying the algorithm we are getting the threshold value from which we are get defect place of the image.

In that the type of the defect image is also displayed, what is the defect type so the proper prevention technique is used to avoid that defect in the fabric.

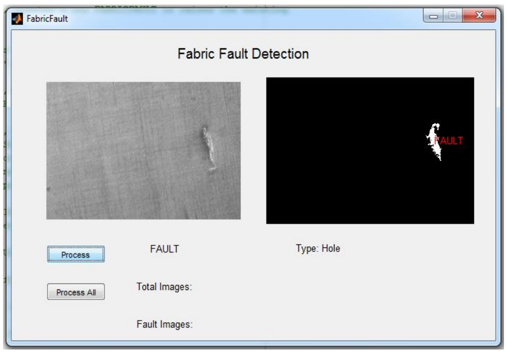

Figure 16: Fault Detection

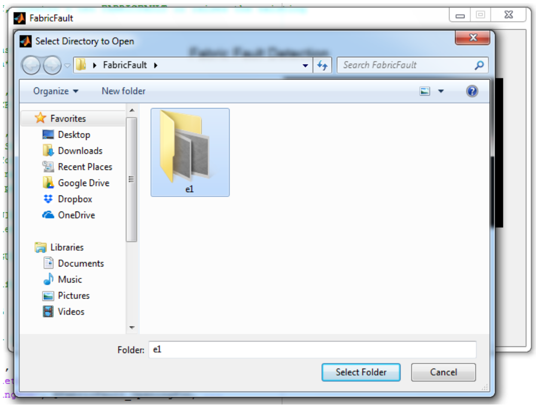

Figure 17: Selecting Multiple Images

In the image 17 the bulk image is selected by selecting a folder and the count of number of defected image in that folder.

Figure 18: Total Count of Faulty Images

5.2 Performance Analysis

Demonstrate the effectiveness of the proposed algorithm. Experiments are executed by using defect-free and defect fabric images taken from TILDA Textile Texture Database [11]. There is the ways to measure the accuracy of detection is detection success rate. Generally, detection success rate, also known as detection accuracy, is defined as

$$\text{detection success rate} = \frac{\text{no. of samples corrctly detected}}{\|w\|\text{total number of samples}} \quad (12)$$

Therefore, fabric detection rate of the proposed algorithm obtained with the images of the TILDA textile are reported in Table.

Table1. Comparison between Existing System & Proposed System

Detection Results	Result of Previous Work [11] Junfeng Jing		Result of Proposed Work	
	Hole	Oil Spot	Hole	Oil Spot
Overall Detection	(50/50) 100%	(50/50) 100%	(50/50) 100%	(50/50) 100%
True Detection	(48/50) 96%	(47/50) 94%	(49/50) 98%	(48/50) 96%
False Detection	(2/50) 4%	(3/50) 6%	(1/50) 2%	(2/50) 4%

The results listed in Table show that the false detection rate of hole, oil spot are 2%,4%. These results indicate that the proposed algorithm achieves better performance in terms of false detection rate. The true detection rate of hole & oil spot 98% & increases up to 98% & 96%. In general, our algorithm performs better in almost all cases.

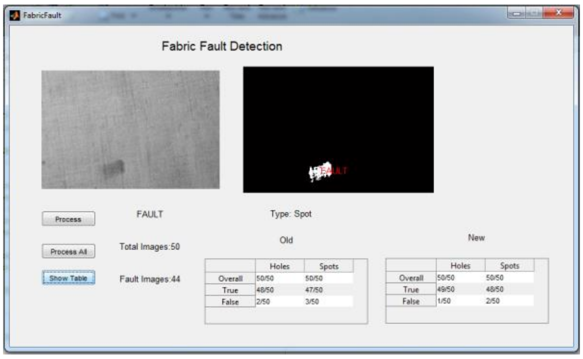

Figure 19: Final GUI Output

VI. SUMMARY AND CONCLUSIONS

In this article, a supervised defect detection approach to detect a class of fabric defects has been demonstrated. The performance of the proposed approach based on multiple LDA and Gabor filters has been evaluated by utilizing fabric images of the TILDA Textile Texture Database. The multiple LDA have been used to extract texture features and Gabor filters has been used for nonlinear dimensionality reduction to achieve more accurate fabric defect detection. A supervised method includes training and detection. In the training section, Gabor filter ge(x,y) could be supervised by a defect-free image IM(x,y).

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In the objective function E. When objective function E reaches the minimum, optimal Gabor filter parameters can be obtained from applied Gabor filter ge(x,y). In the detection section, selected optimal Gabor filter would be applied in defect detection on corresponding defective fabrics. Perfect detection results can be fulfilled on textile fabrics, especially defect detections on patterned fabric present good results in this work, which are fractionally done in research works. Parameters from optimal Gabor filters simultaneously are enumerated in this article and offer references for research on fabric defect detection in future.

In the proposed approach, the true detection rate of the basic algorithm has been tested. Some optimization solutions have been compared with each other and the optimal operational parameters for four kinds of defect yarn types have been found. The tests conducted on different types of defects and different kinds of fabrics have yielded promising results, which have shown that this method achieves a high true detection rate and a low cost for online fabric inspection successfully.

This investigates the feasibility and effectiveness of using high-order local pattern for face description and recognition. A Local Derivative Pattern (LDP) is proposed to capture the high-order local derivative variations. To model the distribution of LDP micro-patterns, an ensemble of spatial histograms is extracted as the representation of the input face image.

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AUTHOR PROFILE

B. G. Chhapkhanewala, Pursuing Master of Engineering in Computer Engineering from Datta Meghe College of Engineering, Airoli, Mumbai University. Completed Bachlor of Engineering in Computer Science & Enginnering, Shegaon, Amravati University.

Dr. S. L. Vaikole, Associate Professor in Datta Meghe College of Engineering, Airoli(Thane)-400708.