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Automated Fabric Fault Detection System

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Abstract*: An effective defect detection scheme for textile fabrics is designed in this paper. 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 defective fabric images to be detected have the same texture background with corresponding defect-free fabric images. The novel high-order local pattern descriptor, local derivative pattern (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-order local derivative direction variations, which can be more detailed information than the first-order local pattern used in local binary pattern (LBP). The significance of the proposed approach lies in selecting Gabor filter parameters with an abundance of choices to build the optimal Gabor filter and achieving accurate defect detection on patterned fabric. High success rate and accuracy with little computational time online are obtained in the defect detection on fabrics, which indicate that the suggested method can be put to use in practice.

Index Terms*: Fabric Fault Detection, Local Derivative Pattern (LDP), Gabour Filter, Loacl Binary Pattern(LBP).

I. INTRODUCTION

Defect detection is a key problem in quality control for many industrial fields like wallpaper scanning, ceramic flow detection and fabric inspection. As for a long time the fabric defects inspection process is still carried out with human visual inspection, and thus, insufficient and costly. Therefore, automatic fabric defect inspection is required to reduce the cost and time waste caused by defects. Many techniques have been developed for detection of defects for fabrics through the years using neural networks, Fourier Transform, Edge Detection, Fractional Dimension, Gabor filter, Wavelet Transform, Model-Based clustering, Fuzzy Logic and many more. However, some of the methods mentioned above are mainly designed for un-patterned fabric inspection.[1]

In textile industry, fabric production is usually done on weaving and knitting machines. Fabric is produced from textile fibers. Textile fibers are generally manufactured with natural element such as cotton. A fabric defect corresponds to a flaw on the manufactured fabric surface. In particular, fabric defects result from processes such as machine defects, faulty yarns, machine spoils and extreme stretching. More than 70 kinds of fabric defect are defined by the textile industry. Most of defects occur either in the direction of motion or perpendicular to it. In terms of quality standards, the defects on the fabric surface are categorized into two: surface color change and local texture irregularity.

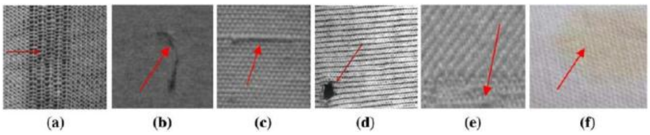

Figure 1: Example defects namely (a) needle breaking, (b) weft curling, (c) slub, (d) hole, (e) stitching (f) rust stains. (Arrows point to defective regions.).

Fabric defect detection is the determination process of the location, type and size of the defects found on the fabric surface. Generally, human inspection is used for fabric defect detection. It provides instant correction of small defects, but human inspection cannot detect errors due to carelessness, optical illusion and small defects. However, human inspection fails on detection defects in terms of accuracy, consistency and efficiency, as workers are subject to boredom and thus inaccurate, uncertain inspection results are often occurred.[2] Thus, automated fabric inspection becomes an efficient method forward to improve fabric quality.

A.Motivation

Nowadays, with the rapid development of computer and image processing technology, computer vision has been widely used in textile industrial production. Thus, automated fabric defect detection becomes a natural way to improve fabric quality and reduce labor costs. Texture classification methods, either explicitly or implicitly, assume that the samples to be classified are identical to the training samples with respect to spatial scale, orientation and gray scale properties. However, real world textures can occur at arbitrary spatial resolutions and rotations and they may be subjected to varying illumination conditions.

This has inspired, which generally incorporate invariance with respect to one or at most two of the properties spatial scale, orientation and gray scale, among others. Flaws on textile fabrics have a great influence on selling price and price reduction ranges from 45% to 65% in the original price of a product. At present, artificial detection occupies main position in the real fabric detection but has a lower detection success rate at the slower speed of 1520 m/min [3]. It is investigated that the accuracy of artificial detection is merely 60% to 70%.

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B. Application of Automated Fabric Fault Detection System

It gives a good running time especially for the real time applications. Texture analysis is important in many applications of computer image analysis for classification, detection, or segmentation of images based on local spatial variations of the intensity or the color. In the other hand defect detection is an important problem in fabric quality control process. At present the quality inspection process is manually performed experts. Therefore, automation of visual inspection tasks can increase the efficiency of production lines and improve the quality of the products as well. Numerous algorithms are currently proposed in fabric detection. Fabric detection approaches are classified into the statistical, the model [4] and the spectral [5, 6].

The statistical approach is based on texture features of fabrics and is defined as a measurement of energy [7] in a window of each fabric pixel. Texture are useful in a variety of applications and has been a subject of intense study by many researchers. Recognition of homogeneous image regions using texture properties is a very important application. 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.

(a) (b)

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

II. METHODOLOGY

In this section, describes the method. 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, then the filtered images are divided into a large number of non-overlapping sub-blocks.

Afterwards, we make data fusion of the corresponding sub-blocks divided from fabric images and the high-dimension data of fused sub-blocks feature vectors is reduced by Gabor filters, then the median filtering and similarity comparison are operated on the low-dimension feature vectors. Finally, the SVM classifier to classify the defected image from the defect free image.

A. Image Acquisition

Various ways are provided to capture image. Some are described as two dimensional-CCD, line scan camera where element 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 camera are costing too much, so inspection algorithm can be approached.

We have chosen to work with TILDA database, elaborated by the Technische Universitt Hamburg in 1995, which consists in 4 different textiles.

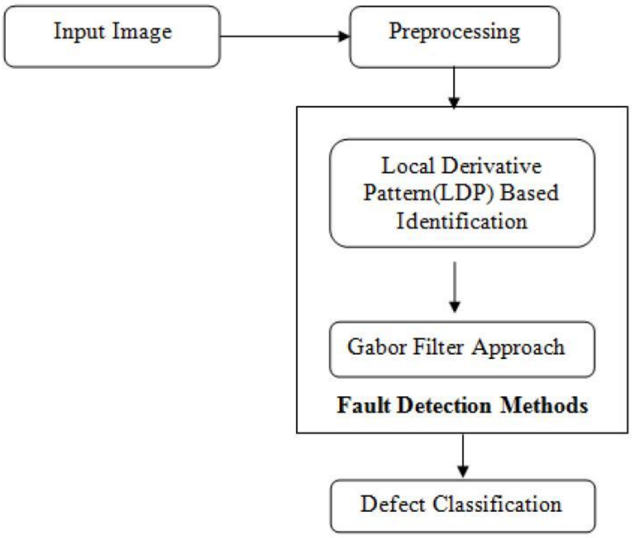

Figure 3: Flowchart of proposed methodology

B. Data Pre-processing

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.

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 camera are costing too much, so inspection algorithm can be approached.

C. Feature Extraction

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.

1) Local 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.

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The LBP features is that a face can be seen as a composition of micropatterns [1]. LBP in nature represents the first-order circular derivative pattern of images, a micropattern 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 grayscale 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.

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

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

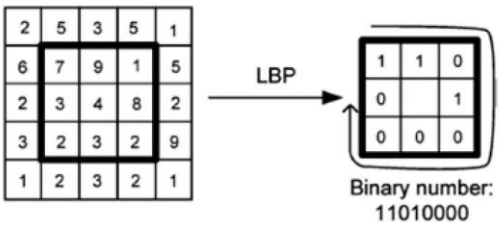

Figure 5: Example of obtaining the LBP micropattern for the region in the black square.

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 derivative binary result while LDP encodes the higher-order derivative information which contains more detailed discriminative features that the first-order local pattern (LBP) can not 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 Z_i, i=1,....,8 be the neighboring point around Z_0 (see Fig. 1). The four first-order derivatives at Z =Z_0 can be written as

$$I^j_{0^0}(Z_0) = I(Z_0) - I(Z_4) \tag{2}$$

$$I^j_{45^0}(Z_0) = I(Z_0) - I(Z_3) \tag{3}$$

$$I^j_{90^0}(Z_0) = I(Z_0) - I(Z_2) \tag{4}$$

$$I^j_{135^0}(Z_0) = I(Z_0) - I(Z_1) \tag{5}$$

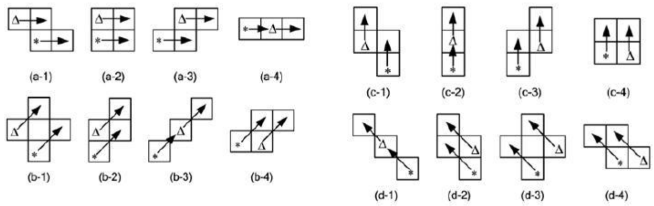

Figure 6: Illustration of LDP templates.

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.

2)Gabor 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 . Meanwhile, Gabor function is modulated by 2-D Gaussian function which involves three parameters in spatial domain. The parameters are expressed as (x; y) and orientation which rotates the values x and y to the corresponding x1 and y1, and

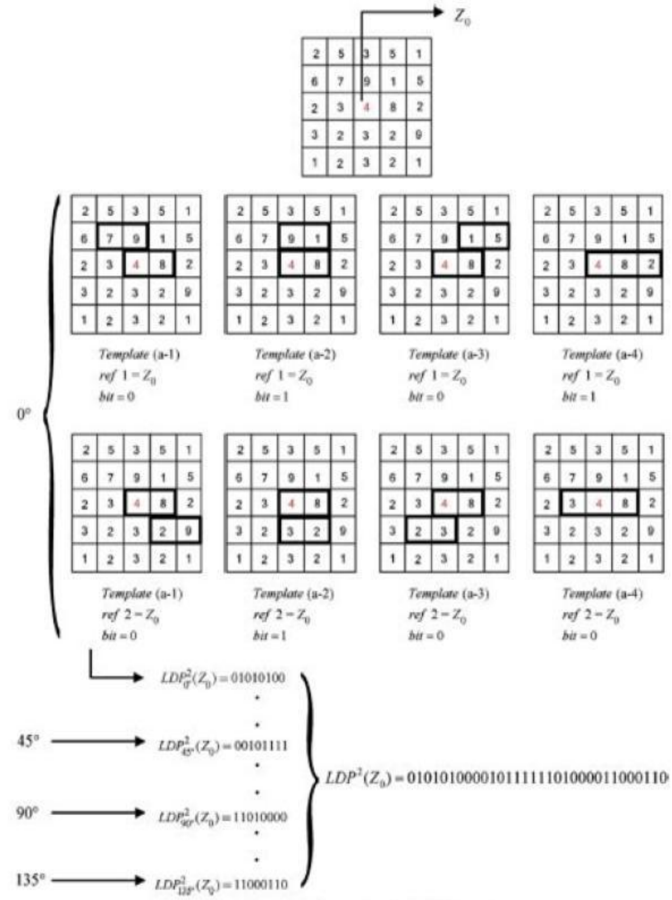

Figure 7: Example to obtain the second-order LDP micropatterns.

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:

$$g(x, y) = \frac{1}{2\pi\sigma_x\sigma_y} \exp\{-\frac{1}{2}\frac{x^{l\,2}}{\sigma_x} + \frac{y^{l\,2}}{\sigma_y}\} \exp(j2\pi u_0 x^l) \tag{6}$$

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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 imag-inary part of 2-D Gabor function indicated as equ-ation (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).

$$g(x,y) = g_e(x,y) + jg_0(x,y) \tag{7}$$

$$g_e(x,y) = \exp\{-\frac{1}{2}\frac{x^l}{\sigma_x}^2 + \frac{y^l}{\sigma_y}\}\cos(j2\pi u_0 x^l) \tag{8}$$

$$g_0(x,y) = \exp\{-\frac{1}{2}\frac{x^l}{\sigma_x}^2 + \frac{y^l}{\sigma_y^2}\}\sin(j2\pi u_0 x^l) \tag{9}$$

D.Support Vector Machines (SVM) classifier

A SVM works by building a hyperplane or set of hyperplanes in a high dimensional space, used for classification. If the hyperplane 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.

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

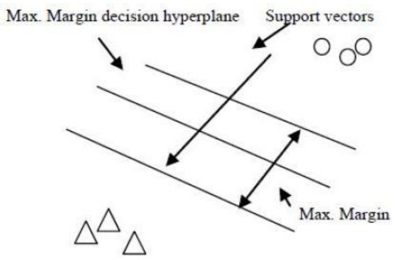

Figure 8: Showing maximum margin between two hyperplanes separating two classes

1)Binary Classification

Given training data (x_i, y_i) for i = 1 ...N, with x_i R_d and y_i 1, 1, learn a classifier f(x) such that

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

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

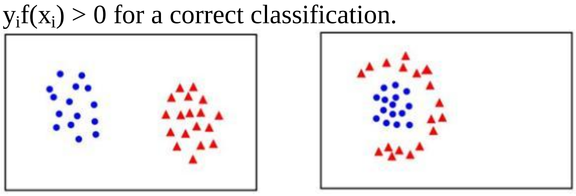

Figure 9

2)Linear classifiers

A linear classifier has the form f(x) = wT x + b.

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

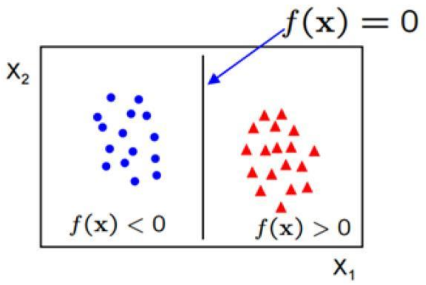

Figure 10

What is the best w?

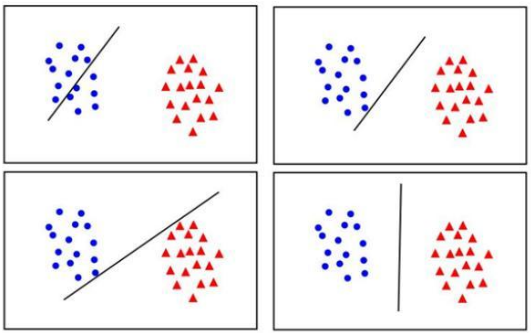

Figure 11

3)Support 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 w^T x+ + b = +1 and w^T x + b = 1 for the positive and negative support vectors respectively.

Then the margin is given by

$$\frac{w}{\|w\|}.(x_+ - x_-) = \frac{w^T(x_+ - x_-)}{\|w\|} = \frac{2}{\|w\|} \tag{11}$$

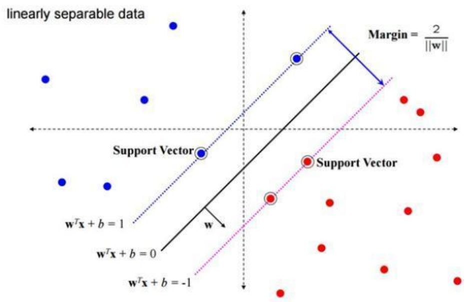

Figure 12: Support Vector Machine

E. Recognition

Using the feature data 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 feature whereas non-fault images tend to have many small features. We use this data to recognize whether the image is of a faulty fabric.

III. EXPERIMENTAL RESULTS

In the proposed system, we are giving the non-defected image rst to the system to recognize the pattern of fiber. In the given experimental result, the first image Fig 13 is the resultant defect free image where their is no defect detected from the system.

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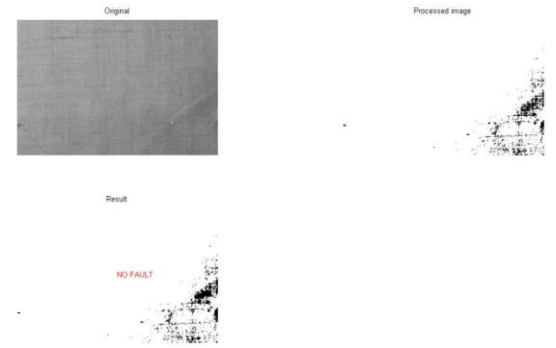

Figure 13: Defect-free

In the Second image Fig 14 their is a small defect is detect by our proposed system. In the image, their is some thread knot present. Which may effect our fabric cost.

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

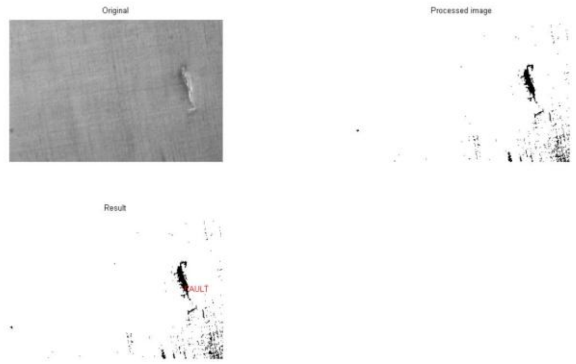

Figure 14: Defected

IV. SUMMARY AND CONCLUSIONS

A supervised method has been proposed in this article including training and detection. In the training section, Gabor filter ge(x,y) could be supervised by a defect-free image IM(x,y) 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.

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 micropatterns, an ensemble of spatial histograms is extracted as the representation of the input face image. Face recognition based on LDP can be performed by using histogram intersection as the similarity measurement.

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