SURVEY OF DEFECT DETECTION ON PATTERNED FABRICS

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ABSTRACT

The textile industry is mostly concerned with the design, manufacture and supply of fabrics. It is one of the main sources of revenue generated industry. The price of fabrics is severely affected by the defects of fabrics that represent a major risk to the textile industry. A very small percentage of defects are detected by the physical inspection even with highly trained inspectors. Although different types of fabric defects had been referenced in literatures, only a few patterned fabrics have been referenced. Researchers have been better result for minor defects. Automatic defect detection system will increase the defect detection percentage. It is economically profitable. An Artificial Neural Network is used as defect identification model. Digital image processing is the extracted option given as input to the neural network, it identifies the defects. This survey will be discussed about the existing methods for the major defects detection such as hole, broken end, thick bar, thin bar, multiple threading and knots.

Keywords: Fabric defect detection; Inspection process; Automatic defect detection; Digital Image processing; Artificial Neural Network.

I. INTRODUCTION

Textile and garment industries are one of the fastest growing and competitive markets worldwide and form a major part of production, manufacturing, employment and business operations in many developing countries. The changes have increased both yield and quality of fabrics, apart from reducing expenses and labor cost. The majority of the companies are paying more attention on improving their quality of usable finished product and achieving faster production speeds.

This is especially more important in textile materials, as defective fabrics reduce its price significantly. Among the various failures faced by garment industries, fabric faults constitute more than 85% (Sengottuvelan et al., 2008). It is considered as an serious issue, as failure in defect detection may result in warranty claims liability, recalled orders along with loss of customers, all of which affect the growth of the company extremely. According to Srinivasan et al. (1992), the price of defective fabrics (second quality) decreases by around 45% to 65% of that of first-quality fabric. Second quality fabrics that may contain a few major defects and/or several minor structural or surface defects (Chan and Pang, 2000). Thus, in order to gain more profit by producing and selling more first quality fabric, it is essential for textile factories to install advanced machines that can eliminate fabric defects. However, changes in the production processes may lead to introduction of more defects.

Digital Image Processing technique is used to extract the features of patterned fabrics. Image processing techniques will help to production increase in fabric industry; it will also increase the quality of product. They have to detect small factor that can be located in wide area that is moving through their visual field.

Inspection of fabrics forms an important aspect of quality control of automated production process and is needed to scrutinize the quality of fabric. Inspection is an action that involves measuring, examining, testing and gauging the individuality of fabric and comparing the results with the specification to establish whether conformity has been achieved for each characteristic. One another important aspect of inspection is defect detection, which is the act of identifying abnormalities that spoils the aesthetics (clean and uniform appearance of the fabrics) and affects inspection parameters like dimensional stability. An expert in human visual inspection can only catch around 60% to 75% of the significant defects (Mak et al., 2012). Also, the detection results are usually not accurate. According to Sari-Sarraf and Goddard (1999) and Kumar (2003), even the most highly trained and qualified inspectors can identify only about 70% of the defects. Furthermore, textile industries are facing increasing pressure to be more capable and competitive by reducing costs. Therefore, it is highly desirable to automate the process of fabric inspection that can be used to improve the quality of fabrics and garments.

In particular, the study focuses on patterned fabrics, which consists of a repetitive design or decorative designs. The wide usage of patterned fabrics has increased the demand in the quantum of production, which to a great extent, is fulfilled by the mechanization process of textile manufacturing. One important process in fabric automation is quality control, which play a predominant role in the maintenance of standards and is mainly accountable for assessing and identifying whether or not the manufactured fabric is up to the expectation of buyer's requirement. As modern manufacturing processes of these fabrics are not perfect, defective patterns are frequently found on these items. Defect detection on patterned fabric is a challenging task due to the appearance of a repetitive pattern on fabric.

I.1. Fabrics and Patterned Fabrics

Fabrics, defined as textile materials produced through weaving or knitting, play a vital role in human life from prehistoric times and its usage can be traced back over 8500 years. Its varied importance in daily life can be understood from its wide usage in clothing, furnishing, symbolic communication and commerce. It is used for protecting, cleaning, holding things and tie things together. It is a flexible woven material consisting of a network of natural or artificial fibers often referred[12] to as thread or yarn. Fabrics are formed by weaving, crocheting, knitting, pressing or knotting fibers together (felt). Fabrics are categorized according to the raw materials used to manufacture, which can be natural or synthetic (artificial).

Patterned fabrics have many categories and sub-categories among them. For example, a pattern can be a flower or graphic logo on the fabric. The repetitive unit can range from the simplest charter box, dots, to the most complicated multiple flowers, animals or designed patterns. These kinds of fabrics are commonly found in many daily items like wallpapers, ceramic tiles, fabrics, painting, pavement, architecture, netting, ropes, chains, patterned metals, heated windows and other safety critical materials. Different types of fabric patterns are shown in Fig.1.

(a) Frieze Pattern (b) Wallpaper Pattern (c)Crystallographic Pattern

Fig.1 Different type of Fabric patterns

It is composed and constructed by a fundamental unit called lattice (2D grid) that generates corresponding wallpaper group patterns by replication with certain isometrics like translations, rotations and reflections. Usually, a patterned texture is synthesized by applying proper symmetry rules of that lattice. A lattice can be decomposed into a finer component called motif, which can regenerate the entire lattice by applying symmetry rules. Fig.2 shows some examples of patterned fabric and its lattices.

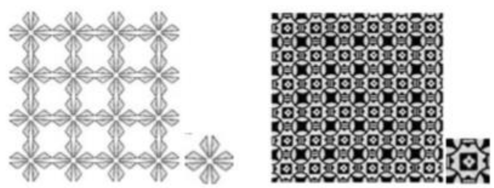


Fig.2 Patterned Fabric and its Lattices

In general, fabrics can be divided into two categories: Non patterned and patterned (Behravan et al., 2011). Non patterned fabrics are usually solid-colored with plain structures. There are many defect detection methods for this type of fabrics, including morphological filter, Fourier transforms, Gabor, wavelet, Markov random field, sparse dictionary reconstruction, neural network, and support vector machine. Patterned fabrics are in periodic variations with complex pattern features. This paper focuses on patterned fabric defect detection.

I.2. Block Diagram of Defect Detection System

The central part of automatic inspection systems is the image processing operations and Artificial Neural Network analysis techniques used. The standard defect detection system consists of five components. The components are (i) Sensing (Image Acquisition) (ii) Preprocessing (iii) Feature Extraction (iv) Defect Detection Scheme (v) Post Processing. The block diagram of defect detection system shown in Fig.3.

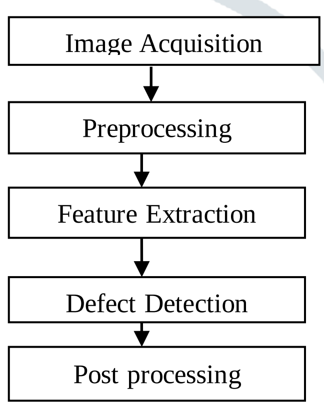


Fig.3 Components of Automatic Fabric Defect Detection System

Image Acquisition: Sensing usually means image acquisition in a defect detection scheme. Different instruments such as line-scan camera, Charge Coupled Device (CCD) camera, and webcam could be chosen as the sensor for an automated defect detection system. These devices are used to digitize the fabric into pixel value of images.

Preprocessing: There are several types of errors due to sensing. First, quantization errors are commonly introduced to an image during its digitization. Second, noise, such as background noise or Gaussian noise, is usually found in the input image due to fold or uneven illumination of lighting. Third, alignment and distortion are two other errors which usually occur in the acquired images. Preprocessing techniques consists of methods that can be used to solve these degradations.

Feature Extraction: In the third step, a set of known features are extracted from the image to characterize a application domain.

Detection: Detection scheme, or called testing stage, is a stage to determine if an input sample is defective or not. This step aims at determining the presence of the defects out of the background.

Post-processing: The last stage of defect detection is post-processing. They reduce false acceptance and false rejection rates and hence, the results are reliable and reproducible.

II. RELATED WORK

S. Anitha and V. Radha [1] compared the performances of three wavelet models in extracting fabric features that are suitable for quality inspection and detection. These three models which include the Tree structured wavelet transform, Gabor wavelet network and the wavelet transform with vector quantized principal component analysis (WTV-PCA) was combined individually with golden image subtraction for fabric defect identification. **Asha, Nagabhushan, and Bhajantri** [2] planned similarity-based strategies for defect detection on patterned textures using five different similarity measures, viz., Normalized histogram Intersection coefficient, Bhattacharyya constant, Pearson Product-moment coefficient of correlation, Jacquard constant and Cosine-angle constant.**Dandan Zhu, Pan, Gao and Zhang** [3] presented a new detection algorithm for yarn-dyed fabric defect based on autocorrelation function and grey level co-occurrence matrix (GLCM). **Elham Hoseini, Farhadi and Tajeripour** [4] introduced a fabric segmentation approach for detecting fabric defects using auto-correlation function. This was done by manipulative the texture primitive template by auto-correlation function from defect-free fabric image in train phase.**Jagrti Patel, Meghna Jain, Papiya Dutta** [5] approached Graylevel texture features extracted from cooccurrence matrix, autocorrelation of sub-images, Karhunen- Loeve (KL) transform, and mean and standard deviations of sub-blocks are used in statistical approaches.**Jing, Yang, and Li** [6] applied a Defect Detection technique based on Patterned Fabrics Using Distance Matching Function and Regular Band. Patterned fabrics were firstly predisposed of by fabric common to form object images mixed with positive and negative pixels while distance matching function was computed to determine the periodic distance of patterned fabrics.**Karunamoorthy.B Dr. D.Somasundareswari, S.P.Sethu** [7] analyzed a novel Image Decomposition technique for patterned fabric inspection which is capable of determining the locations of faulty objects in patterned fabric images with sharp edges. The method applied Artificial Neural Network (ANN) classifier to separate the faulty fabric from the fault-free ones, one sample for each type of defect (for training ANN). **Navneet Kaur** [8] applied Gabor filter scheme. It optimized 2-D Gabor filters to the textile defect detection problem and provided a further support of their suitability for this task. **S. Priya, T. Ashok Kumar and Dr. Varghese Paul** [9] used separate digital images into its bit planes for texture analysis. The contribution made to total image appearance by specific bits is considered here for analysis of clothing defect detection using image restoration and threshold techniques.**Sudarshan Deshmukh, Raut and Biradar** [10] implemented a fabric detection and classification system that was based on Estimating Signal Parameter through Rotational Invariance Technique (ESPRIT) a high-resolution subspace-based method.**D. M. Tsai and S. K. Wu** suggested [11] Auto-correlation function of vertical and horizontal images is used to calculate size of repetitive unit (size of texture primitive template). Then, the grey mean of each pixel is calculated to have primitive texture template.

III. SCOPE AND METHODOLOGY

The patterned fabric detection methods can be classified into four categories: A) Spectral (Gabor) approach, B) Statistical approach, C) Learning approach and Structural approach, D) Model-based approach, E) Texture based approach

A.SPECTRAL (GABOR) APPROACH

The input image is preprocessed using histogram equalization to adjust the contrast of the input image. The lattice is extracted from the template image and the features such as energy and entropy are extracted using the wavelet based method, similarly the features are extracted from the input lattice.

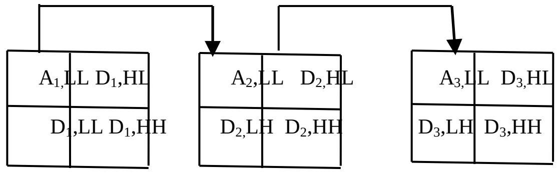
A.1. Optimal tree structured wavelet:

The Optimal tree structured wavelet method combines tree structured wavelet with golden image subtraction TSWT-GIS. The two- dimensional wavelet transform is applied on the input image and is subjected to decompose into four different frequency images as shown in Figure.4. The input image is decomposed into three layers. The number of sub images obtained is depend on the number of layers to decompose, more the number of layers may increase the number of sub images obtained. It is necessary to include criteria to optimize the decomposition level that is calculated based on minimum entropy. The two dimensional wavelet transform is applied on the input image. For each sub-image the energy is calculated. When the sub image size is less than 16 × 16 it may not contain meaningful information and the decomposition may be stopped. The equation of Decomposition of different layers are shown below:

$$E = \sum_{i}^{M} \sum_{j}^{N} H_{ij}^{2} \qquad (1)$$

$$H(z) = -\sum_{I=0}^{255} p(i) \log_2 p(i) \qquad (2)$$

The size of the image is m×n. The features energy and entropy are calculated using the above formula. Energy reflects the homogeneity of the sub image and is defined as follows in equation (1) whereas entropy reflects the measuring of randomness within the sub-image as given in equation (2), where p (i) is the probability of the pixel i in an image.



decomposition of the layers

Fig.4 Schematic diagram of 2-dimensional wavelet transform.

A.2. Gabor wavelet network:

The Gabor wavelet networks method combines gabor wavelet network with golden image subtraction GWN-GIS. Gabor filters have been successfully implemented in various approaches of image analysis and computer vision applications. Gabor filters can well combine both spatial and frequency domain textile information, hence it is suitable for defect detection application. Generally GWN is a combination of Feed Forward Neural Network (FFN), namely Multi Layer Perception (MLP) and the Gabor wavelet decomposition. GWNs represent an object as a linear combination of Gabor wavelets and the parameters of each single Gabor functions (such as orientation, position and scale) are individually optimized to reflect the particular local image structure. GWN is used to take out image feature which can be used in pattern recognition. The past information for the design of optimal Gabor filter is obtained from GWN. The GWN with single defective texture pattern. However, particular layer in selected carefully. The wavelet networks proposed the concept of Gabor Wavelet for solving the 2D problems in pattern recognition, in which an imaginary Gabor wavelet function is used as a transfer function in the hidden layer of the network. The mapping form of the group can be governed by equation (3).

$$f(x,y) = \sum_{i=1}^{N} w_i g^i(x,y) + \bar{f} \qquad (3)$$

where w_i is a group weight from the hidden layer to the output layer and $\overline{f}$ is introduced to eliminate the DC value of an objective function. The imaginary part of the Gabor function is used and it is referred as the modify function, and is expressed in equation (4)

$$g_\sigma^i = \exp\{-\frac{[(x-t_x^t)\cos\theta^2 - (y-t_y^t)\sin\theta^2}{2(\sigma_x^t)^2} - \frac{[(x-t_x^t)\sin\theta^t - (y-t_y^t)\cos\theta^t]^2}{2(\sigma_y^t)^2}\}$$
$$X \sin(2\pi\omega_x^2[(x-t_x^2)\cos\theta^2 - (y-t_y^2)\sin\theta^{2]}) \qquad (4)$$

$$E{=}\min[IM \sum_i w_i g_i] \qquad (5)$$

where t_x^i, t_y^i are the translation parameters of the ith Gabor wavelet,$((\sigma_x^i, \sigma_y^i), \theta^i$ and ω_x^i are the radial frequency bandwidths, the orientation and the central frequency respectively of the ith hidden node. The group of input vector [x, y] is the position of a pixel in a studied image IM, and the output is the grey level of the related pixel. In the group, the five parameters for all of the Gabor wavelet should be calculated by the system learning process, such as
conversion parameters, orientation, radial frequency bandwidth, centre frequency, and its corresponding weight. The objective function of the learning process is defined as given in Equation (5). In fact, the network proposed in [5] has only two input nodes and one output node. In the network, the input vector [x y] is the position of a pixel in the template image, and the output is the grey level of the corresponding pixel. The GWN is offered with a supervised training with the non defective fabric image as the template with the non defective fabric image as the template and it is used to determine the parameters of optimal filter is used to discriminate defective and non defective from the fabric images with the same texture background as in the template image.

B. STATISTICAL APPROACH

B.1. Normalized histogram intersection coefficient

Histogram intersection coefficient counts the common number of pixels of same gray values between two histograms. If p and q are the probability distributions of two images A and B with gray values i = 1, 2, ⋯, N as common random variables, then the histogram intersection coefficient is given by

$$S_{Hist}(A,B) = \sum_{i=1}^{N} \min(p(i), q(i)) \qquad (6)$$

Upon normalizing the coefficient over all gray values, the range becomes (0, 1) indicating that the normalized histogram intersection coefficient (SHist_norm) is 1 if the gray values of the two images exactly match and is 0 if not.

B.2. Bhattacharyya Coefficient

Divergence-type measure between two distributions. If p and q are the probability distributions of two images A and B with gray values i = 1, 2, ⋯, N as common random variables, the Bhattacharyya coefficient is a given by

$$S_{Bhar}(A,B) = \sum_{i=1}^{N} \sqrt{p(i)q(i)} \qquad (7)$$

The Bhattacharyya measure has a plain geometric interpretation as the cosine of the angle between the two N dimensional vectors $(\sqrt{p(1)},...\sqrt{p(N)}^t$ and $(\sqrt{q(1)},....\sqrt{q(N)}^t$. Thus, if the two distributions are identical, we have the following condition:

$\sum_{i=1}^{N}\sqrt{p(i)q(i)} = \sum_{i=1}^{N}\sqrt{p(i)p(i)} = \sum_{i=1}^{N}\sqrt{q(i)q(i)} = 1$ If the two distributions do not match at all, the measure is 0. Thus, the Bhattacharyya measure ranges between 0 and 1.

B.3.Pearson product-moment correlation coefficient

Pearson's product-moment correlation coefficient is another measure of the extent to which signals x = {xi|i = 1, 2, ···, N} and y = {yi|i = 1, 2, ···, N} are related and is given by

$$S_{Pear}(x,y) = \frac{\sum_{i=1}^{N}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{N}(x_i - \bar{x})^2 \sum_{i=1}^{N}(y_i - \bar{y})^2}} \qquad (8)$$

Where, $\bar{x} = \frac{1}{N}\sum_{i=1}^{N} x_i$ and $\bar{y} = \frac{1}{N}\sum_{i=1}^{N} y_i$ It ranges from +1 to −1. The coefficient is 1 when both x and y have positive correlation between them and is −1 when x and y have negative correlation. When there is no correlation between x and y, the coefficient takes the value zero.

B.4. Jacquard coefficient

Measures similarity as the intersection separated by the union of the objects. If two objects are represented in vector form as $\vec{t}_a$ at and $\vec{t}_b$ the Jacquard coefficient compares the sum weight of shared terms to the sum weight of terms that are present in both of the two objects but are not the shared terms. The Jacquard coefficient is given by

$$S_{Jac}(\vec{t}_a, \vec{t}_b) = \frac{t_a . t_b}{|\vec{t}_a|^2 + |\vec{t}_b|^2 - |\vec{t}_a||\vec{t}_b|} \qquad (9)$$

The Jacquard coefficient ranges between 0 and 1. It is 1 when two objects are identical and 0 when the objects are completely different.

B.5. Cosine-angle Coefficient

If two objects are represented as vectors, the similarity of two objects corresponds to the correlation between the vectors. This is specified in terms of the cosine of the angle between the two vectors and is called cosine-angle coefficient. Cosine-angle coefficient is one of the majority popular similarity measures applied to text documents, such as in numerous information retrieval applications. The cosine-angle coefficient between two objects represented by vectors at $\vec{t}_a$ and $\vec{t}_b$ is given by

$$S_{Cos}(\vec{t}_a, \vec{t}_b) = \frac{t_a . t_b}{\vec{t}_a X \vec{t}_b} \qquad (10)$$

where $\vec{t}_a$ and $\vec{t}_b$ are N-dimensional vectors over the term set T = {t_1, t_2, . . . , t_N}. Each element represents a term with its weight in the document, which is non-negative. As a result, the cosine-angle measure is non-negative and is bounded between 0 and 1. When two documents are identical, the cosine similarity is exactly one.

C. LEARNING APPROACH AND STRUCTRAL APPROACH

C.1. Autocorrelation Function

It is an important method to extract the signal period, which describes the autocorrelation degree of random signal between two different moments. According to the autocorrelation, the extraction of signal period can be abled. In this study, autocorrelation function is chosen to extract the pattern point of yarn-dyed fabric. Due to different densities and layouts of color yarns in the warp and weft directions, a yarn-dyed fabric has different periods in both directions. Autocorrelation function of an image in the weft route (Cx,0) and in the warp direction (C0,y) are as follows in turn:

$$C_{x,0} = \sum_{i-1}^{N}\sum_{j=1}^{N} G_{i,j} G_{i-x,j} \qquad (11)$$

$$C_{0,y} = \sum_{i-1}^{N}\sum_{j=1}^{N} G_{i,j} G_{i,j-y} \qquad (12)$$

where x = 1, 2 …, M, y = 1, 2 …, N, M and N are the width and the height of the image; G(i, j) is the grey value of the pixel coordinate (i, j).Defects will demolish the periodicity of yarn-dyed fabric, so the faultless fabric image should be used to extract pattern period. Equation 13 is used to get the grey value of each pixel.

$$Gray=0.299×R+0.587×G+0.114×B \qquad (13)$$

where, R, G and B represent the three components in RGB color model. Then autocorrelation function of the grey image in both directions can be calculated according to equation (11), (12).

C.2. Grey level co-occurrence matrix

Grey level co-occurrence matrix, one of the best capable methods for texture analysis, estimates image properties related to second-order statistics. And it is the basis of analyzing local pattern and the pixel arrangement rules of images. A two-dimensional image can be represented as f(x, y). M and N specify the height and the width of the image, respectively. Current pixel in the image by grey level i and neighbor pixel with grey level j form a pixel-pair. Then the GLCM is generated by counting the occurrences of quantity of pairs between the current and neighbour pixels

Mathematically, the general equation of GLCM parameterized by the offset (dx, dy) is given as:

$$p_{i,j}(d,\theta) = \sum_{x=0}^{M-1}\sum_{y=0}^{N-1}\begin{cases}1, \bar{f}f(x,y)=i and f(x+d_x, y+d_y)=j \\ 0. otherwise\end{cases} \quad (14)$$

where i,j = 1, 2 …, Ng, Ng is the grayscale of the image; the offset (dx, dy) characterizes the pixel displacement and the orientation; d is inter-pixel distance; θ is inter-pixel orientation, that is usually 0°, 45°, 90°, 135°. The yarn-dyed fabric contains color texture, besides structure texture. According to this, defects can be divided into structural type and color type. The former is related to that of the grey fabric, which destructs the structural texture of fabrics, including cracked ends, weft crackiness, stretched warp, holes and so on, but the latter is caused by the wrong layouts of color yarns, which changes color texture of fabrics. Defects will cause the change of the image grayscale distribution, no matter that their types belong to the former or the latter. GLCM can describe the change intuitively.

C.3. Euclidean Distance

Euclidean distance is a commonly used definition of distance. It refers to the actual distance between two points. Euclidean distance is one of the distance measures that can be used to find the dissimilarity between two images. There redundant information in the original images. If Euclidean distance of two images is calculated directly, there will be not only a large amount of calculations to slow down the speed, but the results are seriously affected by noises. GLCM can well describe the fabric texture, thus it is called as characteristic matrix, and the similarity of two fabric images is represented by Euclidean distance of their GLCMs in this study. The Euclidean distance D of GLCMs is as follows:

$$D = \sqrt{\sum_{x=0}^{N-1}\sum_{y=0}^{N-1}[f(x,y) - g(x,y)^2} \quad (15)$$

where, f(x, y) shows GLCM of image to be detected, g(x, y) shows the GLCM of template image, and N is the grayscale of images. The less the value of D, the larger the similarity of two images. The Euclidean distance between the two same images is zero. The detection process is carried out as following steps. Step 1 The pattern period is determined according to the method and through the training, the detection pattern. Step 2 The images to be detected are divided into 16 blocks according to the level of pattern period. Step 3 The GLCMs of being detected images and the template image are calculated with specified parameters. Step 4 The Euclidean distances between them are computed according to Formula (15).In the process of computing GLCM, inter-pixel distance and inter-pixel orientation are two important parameters that will influence the accuracy rate of defect inspection.

C.4. Mathematical Morphology

Mathematical morphology deals with non-linear processes which can be applied to an image to remove details smaller than a certain reference shape called the structuring element. The most commonly used morphological operations used in image processing are dilation, erosion, opening and closing. Binary images are most suited for performing morphological operations. The images obtained after bit plane decomposition are binary images, which are thus suitable for performing morphological operations. Note that bit planes 0 and 1 contain the most significant information regarding the location and shape of the fabric defect. Dilation is an operation in which the binary image is stretched from its original shape. The amount of expansion is controlled by the structuring element. The dilation process is similar to complication, in which the structuring element is reflected and shifted from left to right and then from top to bottom. In this process, any overlapping pixels under the centre position of the structuring element are assigned with 1 or 0 values. If X is the reference image and B is the structuring element, the dilation of X by B is represented as $X \oplus B = \{[(\bar{B})z \cap X] \subseteq X\}$.

where B is the image B rotated about the starting point. When an image X is dilated by a structuring element B, the outcome element Z would be that there will be at least one element in B that intersects with an element in X Erosion is a thinning operator that shrinks an image. The amount by which shrinking takes place is determined by the structuring element. Here, if there is a complete overlapping with the structuring element, the pixel is set white or O. The erosion of X by B is known as $X\Theta B = \{[(\bar{B})z \cap X] \subseteq X\}$.

In erosion, the outcome element Z is considered only when the structuring element is a subset or equal to the binary image X Opening operation is done by first performing erosion, followed by dilation. Opening smoothens the inside of object contours such as breaks, narrow strips and eliminates thin portions of the image. It is mathematically represented as $X^{\circ}B = (X\Theta B) \oplus B$.

Opening operation does the opposite of closing. It is dilation followed by erosion. Closing fills small gaps and holes in a single pixel object. The closing process is represented by $X \bullet B = (X \oplus B)\Theta B$.

Closing operation protects common structures, closes small gaps and rounds off concave comers. Morphological operations are generally used in the detection of boundaries in a binary image. For an image X , the following can be applied to obtain a boundary image

$$Y = X - (X \Theta B)$$

$$Y = (X \oplus B) - X$$

or

$$Y = (X \oplus B) - (X \Theta B)$$

where, the operator $\oplus$ denotes dilation , Θ denotes erosion and '-' indicates the set theoretical subtraction for opening and closing operations . Most binary morphological operations have natural extensions to gray scale processing. Some, like morphological reconstruction, have applications that are unique to gray scale images, such as peak filtering.

D. MODEL-BASED APPROACH

D.1. Regular Band-based Methodology

Regular band is a new pattern-texture determined inspection technique. This technique is constructed on the impression of periodic synchronization. This methodology helps in identifying defects with the help of change in pixel intensities such as fragmented end or dense bar. This technique uses only one parameter i.e. the duration of a period. And this method also outlines the defective portion of fabric in the final image. The regular band method consists of two sub bands; Light Regular Band (LRB): It is used to detect the lighter defects that become sometimes not possible to detect. Dark Regular Band (DRB): It is used to detect the darker defects on different types of fabrics.

Light Regular Band: At the defective region the original moving average (Avg) is greater than zero and standard deviation (SD) is smaller. The severity of defect (M) is calculated by using the formula: M= |Avg-SD| + SD. Dark Regular Band: At the defective region the original moving average (Avg) is less than zero and standard deviation (SD) is smaller. The severity of defect (M) is calculated by using the formula:M=|Avg+SD|-SD

D.2. Methodology of Digital Image Analysis

Digital image processing technique is used to estimate the fabric pills. This technique is related to find out the pills and measure its average intensity on the basis of three criteria's such as heights, volumes and surface. The result is shown on the center of number of revolutions and pills oriented fabric quality. This method was only implemented in pure cotton fabrics. To distinguish the pilled area in fabrics, three stage procedures are followed as shown in Fig.5.

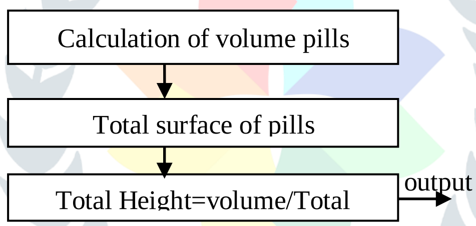


Fig.5. Digital Image Analysis 3-Stage Procedures

First step is related to the calculation of piles volume which is actually the aggregate value of elements in matrix. Then the total surface of pills is identified. This is completed by summing up all defects from the matrix. In last stage calculate the mean height is calculated using below given formula.

Mean Height= Volume/Total Surface (16)

D.3. Usage of Computer-Vision and Artificial Neural Network

This approach is a combination of computer vision and artificial neural networks. Considering the defect recognizer that implements the concept of computer vision. This defect recognizer is trained to detect 4 types of major defects such as hole, thick bar, knot and multiple threading fabric defects. After that gathers the input for the neural network configuration. Firstly any image capturing device captures the images of fabric. After acquisition phase translate the RGB image into binary image through image restoration and threshold process. This output image contains the defected portion along with the other objects. The output is constantly consumed as an input by neural network process. This network classifies the defected portion out of the fabric material.

E. TEXTURE BASED APPROACH

Based on this, the new approach presented in this method consists of 4 steps: computing the texture primitive template, enhancing the defected area, constructing the mean image and segmenting this by an Otsu's threshold approach. On the basis of this method, the introduced defect pattern behaves as a binary image which the black background demonstrate defect free texture and white regions indicate local and shape of defect zones in fabric texture.

E.1. Calculating Texture Primitive Template

Fabric image has a periodic texture. This image is made of patterned rows and columns which are repeated along the image of the fabric according to the size of repetitive unit of fabric texture. Auto-correlation function is used to calculate size of repetitive unit (size of texture primitive template). Equation (17),(18) shows auto-correlation function of vertical and horizontal images.

$$C_{x,0} = \frac{\frac{1}{M*(N-x)}\sum_{i=1}^{N-x}\sum_{j=1}^{M} G_{i,j} * G_{i-x,j}}{\frac{1}{M*N}\sum_{i=1}^{N}\sum_{j=1}^{M} G_{i,j^2}} \quad (17)$$

$$C_{0,y} = \frac{\frac{1}{N*(M-y)}\sum_{i=1}^{N}\sum_{j=1}^{M-y} G_{i,j} * G_{i,j+y}}{\frac{1}{M*N}\sum_{i=1}^{N}\sum_{j=1}^{M} G_{i,j^2}} \quad (18)$$

In above formulas, M×N is size of original defect free image in train phase, Gi, is gray value of pixel (i,j), Cx,0 and $C0,y$ are auto-correlation values of axes X and Y, respectively. T_x and T_y , periodicity of the vertical and horizontal directions, give size of the texture primitive. Texture primitive template is considered after getting the size of texture primitive. In train phase, defect free fabric image is divided into $T_x \times T_y$ blocks, (Zero-padding could be used, if division cause to create smaller blacks). Then, gray mean of every pixel is calculated according to equation

$$M_{i,j} = \frac{1}{n}\sum_{k=1}^{n} W_{ij}^{k} \quad (19)$$

where $M_{i,j}$ is gray value of each pixel in primitive texture template, $W_{i,j}^{k}$ is gray level value of pixels in the k_th block and n is total number of blocks. (In summary, to calculate gray value of pixel (i,j), it must be compute the mean gray value of all pixels corresponding to (i,j)th index in each block and assigns to (i,j)th pixel in primitive texture template).During this way, sizes and values of the primitive texture template is resulted.

E.2. Structure of the Mean Image

Because of the existence of high frequency noises, the better image cannot directly segmented into binary image. One method to filtering these noises through structure of the mean image is presented in this method. At the first step of this method, the enhanced image is partitioned into 8×8 sub-image (Experiments show that this dimension obtains more performance than the others). The mean of all sub-image is calculated via this formula:

$$MV_{i,j} = \frac{1}{64}\sum_{m=0}^{7}\sum_{n=0}^{7} G_{i+m,j+n} \quad (20)$$

in this formula, MVi,j is a pixel that its value is the mean of linked sub – image. In the other words, constructed image is smaller than enhanced image (width (length) size is equal to number of windows in horizontal (vertical) side) and the gray level related to (i,j) pixel, is equal to mean of (i,j) th sub-image gray levels that its size is 8×8 in enhanced image (If necessary the zero padding approach is used). Then to enlarge this image to the original size using a bilinear interpolation mechanism is used. The high frequency noises can be attenuated efficiently by the mean image.

IV. CONCLUSION

In order to understand the formation and nature of the defects, it is important to be able to accurately localize the defective regions rather than classify the surface as a whole. The review of fabric defect detection methodologies using image processing techniques gives us possible trend of this application area. These available techniques were classified into three categories: statistical, spectural and model based. Although the research on visual inspection is varied and ever changing. The above category of approaches gives different results and hence the combination of the approaches can give better results, than either on individually and is suggested for future research.

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