Fabric Texture Analysis and Weave Pattern Recognition by Intelligent Processing

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***Abstract*— Coimbatore is a major city in the Indian state of Tamil Nadu located on the banks of the Noyyal River surrounded by the Western Ghats. It is one of the biggest centers of textile manufacturing in India. A fast-growing metropolitan area city, it is home to over 25,000 textile and manufacturing companies and has spawned many new centers of textiles around it. Textile fabric automation and manufacturing has been of great concern over the past decade. This is a remarkable task because of the accidental changes of fabric material properties. Due to the increasing demand of consumers for high-quality textile products, an automatic and objective evaluation of the fabric texture appearance is necessary with respect to geometric structure characteristics, surface, and mechanical properties. The precise measurement of the fabric texture parameters, such as weave structure and yarn counts find wide applications in the textile industry, virtual environments, e-commerce, and robotic telemanipulation. The weave pattern and the yarn count are analyzed and determined for computer simulated sample images and also for the scanned real fabric images. 2-D integral projections are used to identify the accurate structure of the woven fabric and to determine the yarn count. They are used for segmenting the crossed areas of yarns and also to detect the defects like crossed area due to the random distribution of yarns. Fuzzy C-Means Clustering (FCM) is applied to multiscale texture features based on the Grey Level Co-Occurrence Matrix (GLCM) to classify the different crossed-area states. Linear Discriminant Analysis (LDA) is used to improve the classifier performance.**

***Index Terms*—FCM; GLCM; LDA; Weft and Warp.**

I. INTRODUCTION

The interlacing of the warp ends, and the weft picks referred to as weave. A weave repeat can be shown in the square or grid paper design. A weave replication is the least number of threads required to show all of the interlockings in the pattern. It is usually considered adequate to show one repeat only. Two sets of mutually perpendicular and interlaced yarns, warp and weft, results in the formation of wave repeat.

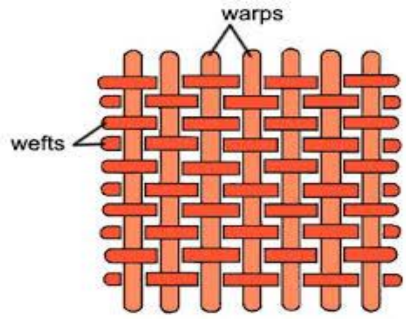


Figure 1: The weft and the warp

The long vertical yarns that are warped around the looms are the warps. The horizontal yarns that are woven through the warp yarns are the wefts and are shown in Figure 1.

Texture analysis finds application in many areas like textile, industrial, agricultural, remote sensing, and biomedical surface inspection. Also, it finds application in the classification and segmentation of satellite images, segmentation of textured regions in document analysis, identification of defects in textile fabrics, disease identification in human organs, etc. The major problems in the real world textures are not uniform due to changes in orientation, size and other visual appearance. The texture is the replication of image patterns. It may be perceived as regular or irregular, coarse or fine, smooth or rough, directional or non-directional, etc. Generally, the fabric texture is made of the repetition arrangement of warp and weft. Textile fabric materials are used to prepare different categories and types of Fabric products in the textile industry. The various classification of textile fabric is Natural fabric and synthetic fabric.

II. LITERATURE SURVEY

FFT techniques were used in image processing to identify weave pattern, fabric count, yarn skewness and other structural characteristics of woven fabrics [1]. Fabrics with several weave patterns and yarn counts were tested using the FFT techniques. Many textile products appear to have periodic structures, which make themselves particularly suitable for the utility of the FT techniques.

A system was developed to detect both weave patterns and yarn color designs [2]. The total quantity of yarn colors and their arrangements in the fabric are determined from reflected images. An HSV color model combines similar yarn colors. So, the system permits the weave pattern, either colored or solid, and the color design of fabric to be correctly recognized. When locating the crossed area of yarns faults may occur.

A fully automatic method was proposed based on Fourier image-analysis techniques to solve crossed-points-detection problems [3].

A method was proposed using a convolution model and an additive model, in both the spatial and frequency domains and was combined to extract information about the fabric structure by image analysis. It was applicable to fabrics with square and non-square conventional weave repeat [4].

A technique was introduced using neural network and image processing technology for classifying woven fabric patterns [5]. Autocorrelation function was used to determine one weave repeat of the fabric. Challenge is in the selection of the set of training data used for the learning algorithm.

A robust recognition algorithm was proposed for fabric weave pattern recognition [6]. Unsupervised decision rules for recognizing warp and weft floats are developed using a fuzzy c-means clustering method. Three basic weave patterns were clearly identified. However, the presence of weft and warp detection is not certain.

Investigations were made to solve the crossed-states detection problem by analyzing the texture information in the extracted crossed-points [7]. It was applied to the plain woven fabric with and without skewness, and the crossed-states were detected. This non-destructive method was useful in analyzing fabric weave types.

A technique was proposed to recognize the fabric nature and type of the main weaving texture [8]. The co-occurrence matrix was applied to calculate the texture characteristics, and the Learning Vector Quantization Networks (LVQN) was used as a classifier to categorize the fabric nature and the type of weaving texture. The classifier performance depends on the lighting condition and also on the image scale.

An automatic method was used for woven textile structure recognition in fiber-level [9]. Weft yarn and warp yarn crossed-area segmentation were performed through a spatial domain integral projection approach.

Classifier-based texture analysis was proposed for woven fabric images for the recognition [10]. In the pattern recognition phase, three methods were tested and compared: Gabor wavelet, local binary pattern operators and Gray-Level Co-Occurrence Matrices (GLCM). Classification is done using Support Vector Machine. The fusion of the Gabor wavelet and GLCM were done to improve the accuracy, but GLCM has better running time.

A technique was proposed for weave pattern recognition method for computer-simulated woven samples and real woven fabric images [11]. To evaluate the accuracy of FDFFT, standard roughness parameters from the 3-D fabric surface were determined. FDFFT was concluded as a fast parameter for fabric roughness measurement based on 3-D surface data.

A review was provided about the identification of woven fabrics developed in nearly 3 decades starting from the mid-1980s until now [12]. The objective evaluation technology based on image processing and artificial intelligence holds the advantages of quick response, digital solution and accuracy compared with the manual method based on human eyes and experiences. Both the merits and demerits of frequency domain analysis-based and spatial domain analysis-based methods have been discussed.

Mahajan Archana B., et al. proposed a technique for textile defect identification and classification based on computer vision. Wavelet frames are used for feature extraction with the design of neural network classifier. Then sub-image based PCA method is applied for data classification. The defects are classified using neural networks [13].

Azim, G.A. proposed a method based on texture analysis and neural networks to distinguish the textile defects. Feature extraction is done designed based on Gray Level Co-occurrence Matrix (GLCM). A neural network is used as a classifier to recognize the textile defects [14].

Dandan ZHU et al. proposed a new detection algorithm for yarn-dyed fabric defect based on autocorrelation function and GLCM. The autocorrelation function is used to determine the pattern period of yarn-dyed fabric. GLCMs are computed with the specified parameters to portray the original image. Euclidean distances of GLCMs between being detected images and the template image, which is selected from the defect-free fabric, are computed, and then the threshold value is given to realize the defect detection. Accurate detection of common defects of yarn-dyed fabric, such as the wrong weft, weft cracks, stretched warp, oil stain and holes could be known [15].

Xuejuan Kang, et al. proposed an automatic approach to classify the three woven fabrics: plain, twill and satin weave. 2-D wavelet transform is used to obtain low-frequency sub-image in order to reduce the analysis of fabric images. GLCM and Gabor wavelets are used to extract the texture features of pre-processing fabric images. Probabilistic Neural Network (PNN) is used to classify the three basic woven fabrics. The experimental results show that the novel method can automatically, efficiently classify woven fabrics and obtain exact classification results (93.33%) [16].

III. PROPOSED WORK

The major geometric characteristics of woven fabrics are weave pattern and yarn count. Weave pattern is the weave that is periodically repeated throughout the entire fabric area. Yarn count is the number of yarns per centimeter. The block diagram of the proposed method is shown in Figure 2. Different appearance of fabrics is due to the weave pattern effects on twisting and trimming stiffness of the fabric. Fabric quality is measured using yarn count which is a measure of the quality of the woven fabric.

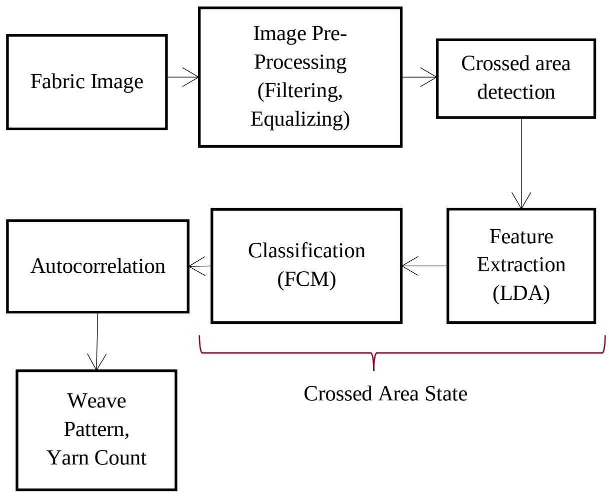


Figure 2: Block Diagram of Automatic Woven Structure Recognition

The proposed method is evaluated using two categories of images. The first one belongs to the woven material images simulated from the computer and the second one to the real images extracted from different fabric images [17].

Computer simulated sample images are shown in Figure 3. It could be observed by inspection that these images have different weave types, fiber appearances, and yarn counts. Simulated woven samples are generated by applying programmable image processing filters.

Figure 3: Computer-simulated images

The real fabric images scanned using HP scanner with a resolution of 2400 dpi is shown in Figure 4. For real fabric scan, it is necessary that the warp and the weft yarns are arranged properly along the x- and y-directions to achieve the best performance for the crossed-area detection. A frequency-domain Butterworth low-pass filter is used for reducing the noise.

Figure 4: Scanned real fabrics images

To detect the interlacing area where weft yarn and warp yarn are crossed over each other, a spatial-domain integral projection approach is applied. Interstices between yarns display darkness. Thus, the pixels surrounding them have relative lower grey levels. The local minima of the horizontal and vertical integral projections can be located from the positions of interstices among yarns. If I(x, y) is an $M \times N$ gray scale image and the horizontal and vertical projection of the entire image is defined, respectively, as $H(y)$ and $V(x)$ given in Equations (1) and (2):

$$H(y) = \sum_{x=1}^{N} I(x,y) \qquad (1)$$

$$V(x) = \sum_{x=1}^{M} I(x,y) \qquad (2)$$

The warp separation lines and weft separation lines are found by finding the local minima of horizontal and vertical integral projections. The intersection of the warp separation lines with weft separation lines are recognized as the crossed areas.

The crossed areas of the weft and warp yarns are detected by subdividing into small image cells, which convey the crossed area detection. The state of a crossed area is analyzed using the texture features of the fabric. GLCM based feature extraction is used in the process. GLCM of an image shows the statistic characteristics of gray level. The eight GLCM texture features that are calculated are:

1) Contrast (CON)
2) Dissimilarity (DIS)
3) Homogeneity (HOM or inverse difference moment)
4) Angular second moment (ASM) or Energy
5) Entropy (ENT)
6) GLCM mean
7) Variance (VAR) and
8) Correlation (COR)

To reduce the recognition errors caused if any, eight texture features with multiple distance d = 1, 2, 4, 6, 8, 10 pixels and four (0, 45, 90, and 135) angular directions are calculated. For each detected crossed area, there are 8 ×6 ×4 = 192 texture features. A feature vector of the detected crossed area is formed by the 192 values. For M × N image segment I(x, y), gray levels, i and j, the non-normalized GLCM P_{ij}s are defined in Equation (3):

$$P_{i,j}(\theta,d) = \sum_{x=1}^{N}\sum_{y=1}^{M} c\{(I(x,y)=i)\wedge(I(x \pm d\theta_0, y \mp d\theta_1)=j\} \qquad (3)$$

where: C{.} = 1, if the argument is true
C{.} = 0 otherwise

The $\pm$ and $\mp$ signs mean that each pixel pair is counted twice: once forward and the next time backward. A feature vector has 192 elements. The GLCM features are interrelated by definition. Additionally, the diversity of the fabric samples also makes the measured feature vectors become confusing. The measured feature vector sets appear clouded and redundant. Hence, the accuracy of the next classification may be interrupted. Linear Discriminant Analysis of the feature vector set is performed for dimensionality reduction and to extract the features. LDA reduces the redundancy in the feature vector sets and increases the signal. For example, in MXN image there are m-crossed areas detected and every detected crossed area is represented by a feature vector with 192 elements.

The feature data set for a material image is a 192 × m matrix X. By using LDA, a new basis B is found that will reveal an optimal representation Y of the original data set X. The row vectors of B will become the linear components of X.B is a linear transform that rotates and stretches X into Y, i.e., BX = Y.

FCM is used to classify the two possible different crossed-area states. To classify a set of texture feature vectors with k dimensions into two clusters. The average horizontal and vertical covariabilities of each classified cluster are computed. A fuzzy-rule-based decision is made for each cluster. The cluster with higher horizontal covariabilities and lower vertical covariabilities is determined as Weft Float, and the other cluster is Warp Float.

The weave pattern is detected as follows: A matrix C, which represents the detected crossed-area states, is formed with 0s and 1s. The fabric sample is assumed to have M warp yarns and N weft yarns. There are M × N crossed areas detected in the fabric sample, the size of C is M × N. Automatic measurement of Yarn Count is performed using FFT. Fast Fourier transform (FFT) is applied to the entire original fabric image, taking advantage of the horizontal and vertical projections, i.e., H(y) and V (x). Consider H(y) and V (x) as the weft profile and the warp profile, respectively. Yarn counts are determined from the 2-D FFT of the profiles.

IV. Simulation Results and Discussion

The proposed methods are evaluated both for computer-simulated samples and real woven fabric images. Preprocessing of the images is carried out and the yarn crossed areas are segmented by a spatial domain integral projection approach. By performing FCM and LDA on GLCM, feature vectors extracted from the segments. The yarn crossed area states are determined based on the texture orientation features, the yarn count is determined by applying 2-D FFT to the integral projections. The manual counts show a slight deviation from the computer-determined yarn count. Simulation outputs for real woven fabric image are shown in the following Figures 5.1 to 5.12. GLCM Texture Features and Yarn Count of the Fabric are shown in Figure 5.13.

Figure 5.1: Input image

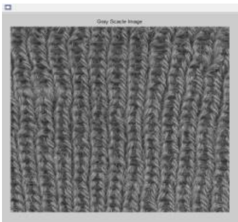


Figure 5.2: Gray scale image

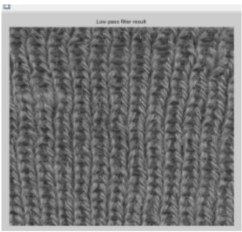


Figure 5.3: Low pass filtered image

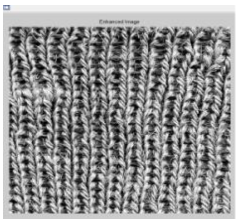


Figure 5.4: Enhanced image

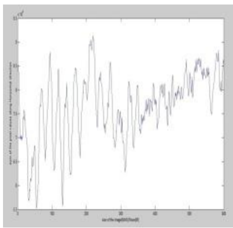


Figure 5.5: Horizontal projection of the gray image

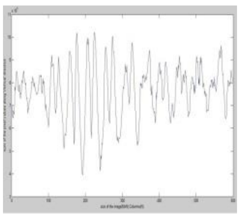


Figure 5.6: Vertical projection of the gray image

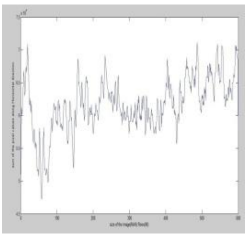


Figure 5.7: Horizontal projection of the smoothened image

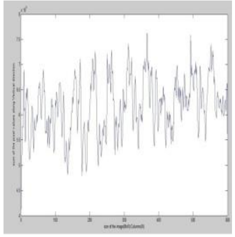


Figure 5.8: Vertical projection of the smoothened image

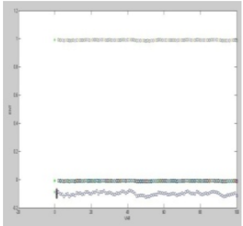


Figure 5.9: FCM clustering

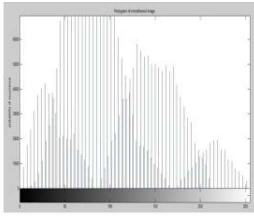


Figure 5.10: Histogram of the smoothened image

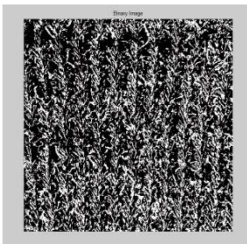


Figure 5.11: Binarized image

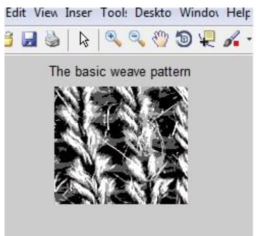


Figure 5.12: Weave pattern detected

Figure 5.13: GLCM texture features and a yarn count of the fabric

A. Yarn Count Verification

To verify yarn, count fabric is being chosen, which is a computer-simulated fabric image, and its yarn count is set to 8. The yarn count program is then applied to the computer simulated fabric image. Finding the yarn count and the related images are shown in Figures 5.14 to 5.22.

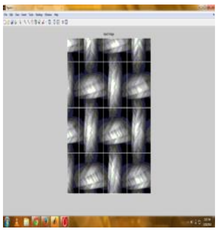


Figure 5.14: Input image

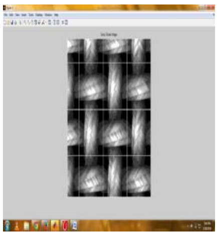


Figure 5.15: Gray scale image

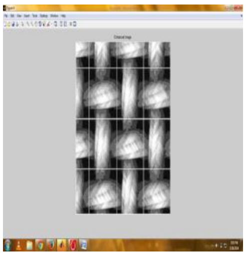


Figure 5.16: Enhanced image

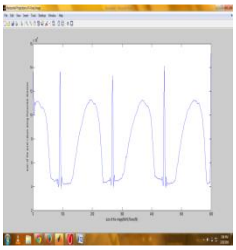


Figure 5.17: Horizontal projection of the gray image

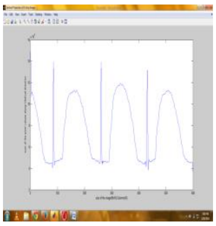


Figure 5.18: Vertical projection of the gray image

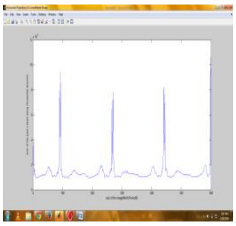


Figure 5.19: Horizontal projection of the smoothened image

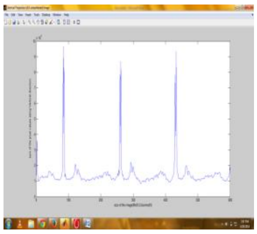


Figure 5.20: Vertical projection of the smoothened image

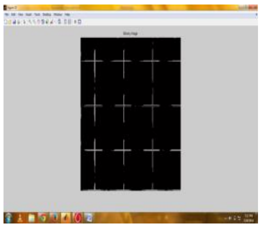


Figure 5.21: Binarized image

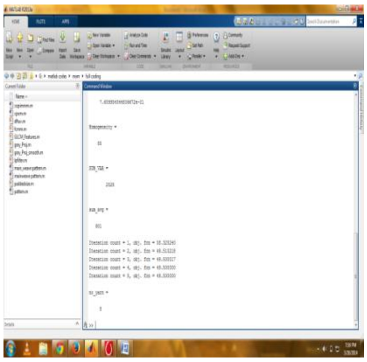


Figure 5.22: Yarn count of the fabric

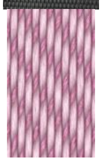
V. CONCLUSION

The proposed method is used to detect weave type, yarn counts and the defect in the weave pattern in fabric samples. The technique is tested by using both the computer-simulated woven samples and real woven fabric images. The test samples with various yarn counts, appearance, and weave types are chosen for testing. All weave patterns of the fabric samples tested are successfully recognized, and computed yarn counts are found to be consistent with the manual counts. Hence it can be concluded that this recognition method allows automatic recognition of basic weave pattern and precisely measure the yarn count.

APPENDIX

Weave Pattern and Yarn Count for Computer Simulated Images and for Scanned Real Fabrics

1. GLCM Texture Features of Computer Simulated Images

S.No	Input Image	CON	ASM	COR	AUTO COR	DIS	ENT	HOM	Mean	VAR	COV_H	COV_V	Yarn Count
1.		536	2	49	2.285772 8539576 37e+01	169	399	52	254 0	900	6.22885 2073043 960e+0 8	1.43497 9424930 440e+07	769
2.		100	5	90	2.496145 7636566 34e+01	63	329	73	253 6	900	1.14551 0917127 852e+0 8	1.75431 7284606 984e+08	65
3.		59	6	94	2.523619 5652173 92e+01	42	308	81	253 9	900	1.23494 9257417 919e+0 6	6.57024 2166029 940e+08	16

S.No	Input Image	CON	ASM	COR	AUTO COR	DIS	ENT	HOM	Mean	VAR	COV_H	COV_V	Yarn Count
4.		128	4	88	2.517845 3177257 52e+01	72	334	72	256 8	904	1.28363 2591587 952e+0 8	1.14039 8385310 824e+08	10
5.		484	2	54	2.314562 7090301 00e+01	154	139	55	254 3	902	1.31823 9250414 580e+0 6	4.96871 1649582 358e+07	492

2. GLCM Texture Features of Scanned Real Fabrics

S.No	Input Image	CON	ASM	COR	AUTO COR	DIS	ENT	HOM	Mean	VAR	COV_H	COV_V	Yarn Count
1.		334	3	68	2.381317 7257525 08e+01	130	384	58	2534	899	4.9362 e+07 1111	1.3611 e+08	629
2.		121	4	88	2.484895 2062430 32e+01	70	335	72	2530	899	7.1985 42652 05075 3e+08	5.3780 321462 17028e +07	83
3.		134	4	87	2.469839 7435897 44e+01	73	339	71	2531	896	1.1621 84561 96259 4e+09	1.5136 127154 57986e +07	156
4.		52	6	95	2.524846 4325529 54e+01	41	301	81	2530	900	1.5120 70897 46907 1e+09	1.0548 319064 77017e +08	511
5.		572	2	46	2.263041 8060200 67e+01	179	403	50	2535	899	2.8985 23886 28798 0e+07	1.0276 575874 26795e +08	109

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