Fabric Defect Detection Using Modified Local Neighborhood Analysis

Maheshwari S. Biradar, P. M. Patil, and B. G. Sheeparamatti

Abstract Fabric defect detection plays a crucial role in the textile industry to improve the quality of service of the fabric texture. Automatic fault detection in fabric is challenging because of the variety of texture patterns, manufacturing defects, defects due to dyeing, and defects due to external environmental conditions. **Existing local neighborhood analysis (LNA) for defect detection has given poor performance for smaller and light color variation defects.** To deal with such conditions, this paper presents the unsupervised modified local neighborhood analysis (MLNA) for finding defect in non-patterned fabric. **The threshold value used for detection of defect depends upon mean, standard deviation, and entropy of local homogeneity measure.** The performance of the system is evaluated on the in-house database based on the percentage defect detection rate. The results of the proposed method are compared with previous methods such as wavelet transform and Gabor transform, **and it is observed that the proposed method detects 97.33% of defects and this is much better than the detection rates of LNAs and other existing methods**.

Keywords Modified local neighborhood analysis · Local homogeneity measure · Fabric defect detection · Non-patterned fabric

1 Introduction

In recent years, the textile industry is booming due to enormous growth in the fashion industry. The fabric material is made up of natural or synthetic threads by weaving, spreading, looping, crocheting, bonding, or knitting. Fabric materials are categorized into patterned and non-patterned fabric images. Fabric is majorly made up of four sources such as a plant (cotton, bamboo, jute, flax), animal (silk and wool), mineral (glass fiber and asbestos), and synthetic (nylon, acrylic, polyester, rayon). Plant,

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animal, and minerals are considered as the natural resources of the fabric raw material. Cotton, bamboo, jute, or flax is obtained from plants [1, 2].

Defect in the fabric causes the irregularity in the pattern and textures of the fabric material which significantly reduces its cost by 45% to 75% in the market. Fabric defect can occur due to fault in the production machine, improper weaving, dyeing, oil, rust, finishing, high yarn tension, missing stitches, and contamination due to external agents such as dead fibers or husk. Common types of defects occurring in the fabrics are double ends, floats, holes, missing ends, thick bar, thin bar, broken pattern, broken picks, cut weft, double pick, gout, snarl, stain, tear, knots, etc. Some of the major fabric defects are shown in Fig. 1. Manual fabric defection is widely carried out for fabric defect detection. But manual fabric defect detection task is inefficient and unreliable because of boredom, tiredness, vision problem, and inattentiveness of the person. This leads to the automatic fabric defect detection system to improve the quality of service of fabric defect detection [3, 4].

In the past, various approaches have been carried out on computer vision-based automatic fabric defection for patterned as well as non-patterned fabrics. Computer vision and image processing play a vital role in the fabric defect detection which captures the fabric images, preprocesses it to remove the artifacts and noises present in the image, and employs computational algorithms to detect fabric defect. Fabric defect detection is categorized into statistical, spectral, model-based, structural, learning-based, and hybrid approaches [5, 6]. Statistical approaches such as auto-correlation models [7] and co-occurrence matrix [8] are simple to implement but

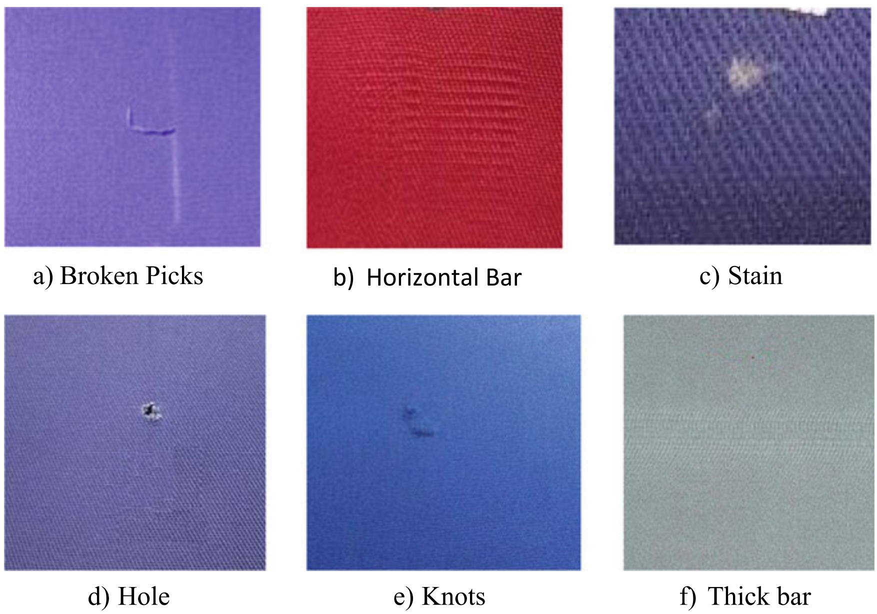


Fig. 1 Fabric defect samples

weak at describing the fine texture of the fabric. Spectral approaches such as Fourier transform [8], wavelet transforms [9], Gabor transforms [10], and contour-let transform [11] can detect and localize the defects effectively but suffering from lower detection rate and higher computation cost. Model-based approaches such as Markov random fields are weak in detecting smaller and light color variation defects in fabric [12]. Neural network-based learning approaches resulted in better detection accuracy for both online and offline modes but lack in reliability and highly complex for parameter tuning during training [13]. Structural approaches are more suitable for defect detection in complex patterns but perform poorly for smaller defects [6]. Hybrid approaches such as Bollinger Band (BB) [14], regular band (RB) [15, 16], and wavelet golden image subtraction (WGIS) [17] are efficient and combine the advantages of various defect detection approaches. Hybrid approaches generally give better results for patterned fabrics and are sensitive to the pattern period and illumination changes. Chengfei Li and Xinhua Chen [18] presented local neighborhood analysis for surface defect detection. They have given more focus on plain surface detection but not given much concentration on various types of texture defects so that cause of defect can be identified. In our previous approach [19], we further implemented local neighborhood analysis (LNA) for fabric defect detection which can deal with distinct fabric defects. In that, threshold calculation which is used to detect the defect depends upon the mean of local homogeneity measure only, due to which it gave a poor performance for the defect caused due to light color variation and smaller defects.

In the proposed method, we have presented modified local neighborhood analysis for the defect detection which can detect the light color variation and smaller defects. In this, the threshold value is dependent on mean, standard deviation, and entropy of local homogeneity measure.

Rest of the structure of paper is described as below: Section 2 depicts the details of proposed methodology. Section 3 describes the brief details about database, experimental results, and discussion. Finally, Sect. 4 concludes the paper.

2 Proposed Modified Local Neighborhood Analysis (MLNA)

The flow diagram of the proposed methodology is shown in Fig. 2 which consists of image preprocessing, local neighborhood analysis, and modified thresholding for the defect detection.

Input color image is converted to a grayscale image to minimize the computation efforts, and grayscale is enough to capture the texture information of the image. Local homogeneity of a grayscale image is measured using the coefficient of variation. The local neighborhood is the measure of regularity of the fabric texture and gives information about the distribution of gray scale. Fabric defect brings the abnormalities in the homogeneity of the defected region. The local homogeneity is computed over

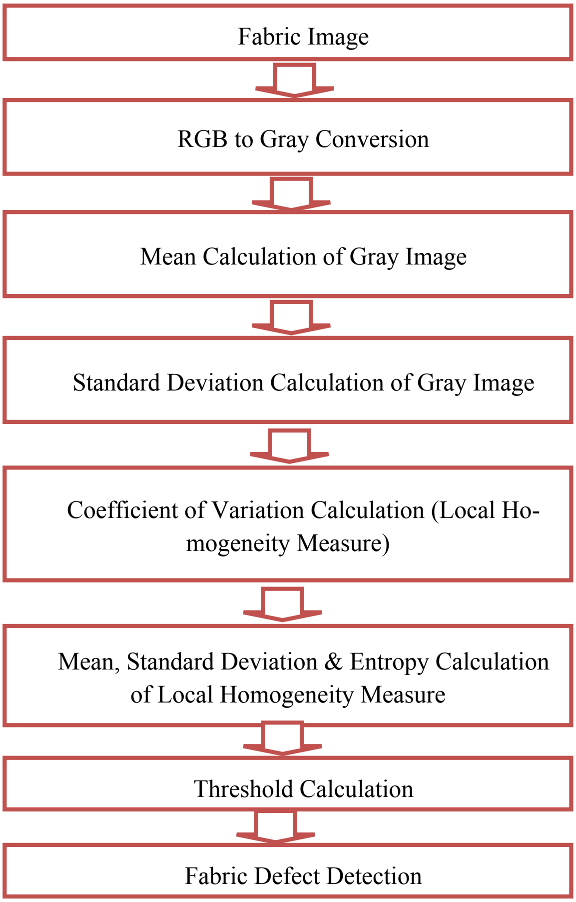


Fig. 2 Proposed system flow diagram

the local region of W x W, where W is given by W = 2w + 1. The coefficient of variation is the ratio of the mean of the grayscale image to the standard deviation of the grayscale image. The mean input grayscale image is computed over the local region using Eq. 1.

$$\mu_{x,y} = \frac{\sum_{i=-w}^{w} \sum_{j=-w}^{w} I(x+i, y+j)}{W \times W} \quad (1)$$

The standard deviation for the grayscale image gives the deviation of grayscale intensity from the mean over the local window and is computed using Eq. 2.

$$\delta_{x,y} = \sqrt{\frac{\sum_{i=-w}^{w} \sum_{j=-w}^{w} \left(I(x,y) - \mu_{x,y}\right)^2}{W \times W}} \quad (2)$$

The coefficient of variation is also called a local homogeneity measure (LHM). The percentage coefficient of variation for the local region is computed using Eq. 3.

$$C_v(x, y) = \frac{\delta_{x,y}}{\mu_{x,y}} \times 100 \tag{3}$$

where M is a total number of rows, whereas N represents a total number of columns, W is the local window, w is the factor that decided the local window, $\mu x,y$ is mean of a grayscale image, $\delta x,y$ is the standard deviation of grayscale image, and Cvx,y is coefficient of variation. In LHA, the threshold value is computed using the mean of local homogeneity measure. In the proposed method, the threshold value encompasses the mean, standard deviation, and entropy of the local homogeneity measure. Entropy gives the measure of randomness of the distribution of local homogeneity measure which helps to characterize the defected and defect-free region. Additional standard deviation and entropy in the calculation of threshold value make it compatible to detect fine and light color variation defects also. The threshold value ($\propto$) for MLHA is calculated using Eqs. 4–7.

$$\propto = \frac{(\mu_{cv} + \delta_{cv} + \varepsilon_{cv})}{3} + w \tag{4}$$

where

$$\mu_{cv} = \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} C_v(i, j)}{M \times N} \tag{5}$$

$$\delta_{cv} = \sqrt{\frac{\sum_{i=1}^{M} \sum_{j=1}^{N} (C_v(i, j) - \mu_{cv})^2}{M \times N}} \tag{6}$$

$$\varepsilon = -\sum P \times \log_2(P) \tag{7}$$

where μ_{cv} is the mean of LHM, δ_{cv} is the standard deviation of LHM, and ε is the entropy of LHM. The defect in the image is detected by applying the threshold to the LHM. The performance of the thresholding is highly dependent upon the control variable w. Rather than selecting random values as a control variable, w is selected as a control variable which is also used as a factor for deciding the local window. If the LHM value is greater than the threshold value, then the region is considered as defected region; otherwise, it is considered as the defect-free region.

2.1 Experimental Results and Discussion

The proposed system is implemented using MATLAB software using Computer Vision Toolbox. The system specification used for the implementation has specifications such as a personal computer with a Core i3 processor, 2.64 GHz processor speed, 8 GB RAM, and Windows Operating Environment. The performance of the system is evaluated on the in-house database of non-patterned fabric textures based on % defect detection rate (DDR) as given in Eq. 8. Our database consists of a total of 450 images which consist of 75 images of the hole, thin bar, thick bar, broken picks, knot, and stain defect each.

$$\%\ DDR = \frac{Defect Detected Samples}{Total Number of Samples} \times 100 \tag{8}$$

Table 1 presents the DDR for various types of defects for distinct window size. Very small window size (W = 3, W = 5) is unable to capture the fine texture of the local region of the image which tends to lower DDR. Larger window size (W = 9, W = 11) loses the fine texture and subsequently resulted in lower DDR. Moderate local window (W = 7) is well suitable for defining the texture of the local region, thus resulting in better DDR.

The performance of MLHA is compared with the simple LHA in , and it is observed that the addition of or standard deviation and entropy in the threshold value calculation significantly improves the performance of MLHA over LHA.

Table 1 Defect detection rate (%DDR) for various defects

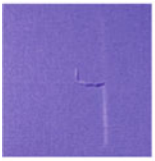
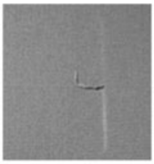
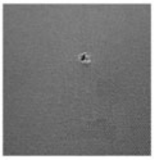
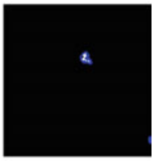
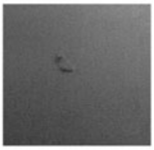
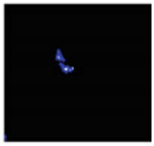
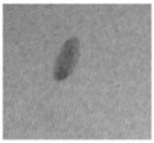
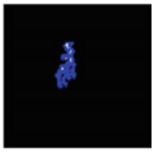
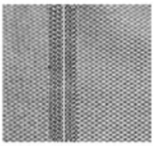
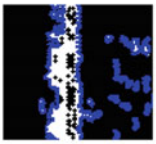
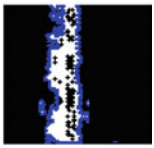
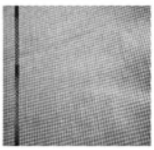
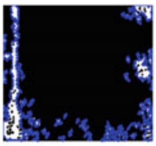
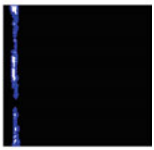
Defect type	% Defect detection rate (DDR)				
	$W = 3$	$W = 5$	$W = 7$	$W = 9$	$W = 11$
Hole	85.33	96.00	98.67	93.33	81.33
Thin bar	84.00	92.00	97.33	89.33	70.67
Thick bar	86.67	90.67	97.33	92.00	77.33
Broken picks	82.67	94.67	98.67	88.00	74.67
Knots	88.00	92.00	97.33	92.00	78.67
Stain	74.67	90.67	94.67	85.33	69.33
Average DDR (%)	83.56	92.67	**97.33**	90.00	75.33

Table 2 Comparison of overall % DDR of MLNA with the previous methods

Method	% DDR
Wavelet transform [20]	94.00
Gabor transform [10]	95.00
LNA	96.40
MLNA	97.33

The experimental results for the proposed system for different kinds of defects are shown in Table 3. It shows that MLNA gives a precise defect outline than the simple LNA. The proposed method resulted in average Jaccard index (JI) of 0.87 for all types of fabric defects.

Table 3 Experimental results for various defects

Defected Image	Gray Scale Image	Defect Detection (LHA)	Defect Detection (MLNA)
			
			
			
			
			
			

3 Conclusion

Thus, in this work modified local neighborhood analysis is proposed for the fabric defect detection. The threshold value is dependent on mean, standard deviation, and entropy of local homogeneity measure. The proposed algorithm is simple to implement and faster and can be used for online fabric defection. It can detect the smaller, light color variation and stain defects. The proposed system resulted in a 97.33% defect detection rate which is better than the simple local neighborhood analysis. In the future, the proposed system is planned to use for patterned fabric defect detection.

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