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Textile Fabric Defect Detection Based on Selective Wavelet Approximation

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Abstract: The applications of Visual Inspection System is used in commercial and industry like a wide spectrum. There are many algorithms propounded for defect detection in textile fabrics. This research work is related with such an algorithm of identifying defects in textile fabric. In this study, researchers have used wavelets for eliminating the texture background of the images for isolating the defects. Later an algorithm is deployed based on pixel homogeneity and intensity variation to segment the defects. This is one of the algorithm which identifies the texture defects based on non texture techniques. The algorithm is suitable for high texture background images. The results of the algorithm is compared with Morphological Analysis Method and wavelet Reconstruction Method. The algorithm is capable of detecting any broken edges in the fabric pattern.

Key words: Wavelet, segmentation, texture, approximation, edges

INTRODUCTION

Recently the visual inspection systems in industry has played a prominent role in ensuring the quality of the products. The texture defect detection such as cracks identification, discontinuity and stains has emerged into forefront position recently in industry.

Already there are many texture defect detection algorithms but it uses complicated procedures such as K-means clustering, adaptive wavelet transformation (Han and Shi, 2007). Many methods for defect detection has been propounded including patterned fabric defect detection (Ngan *et al.*, 2005), defect detection using segmentation (Bhalerao and Wilson, 2001), wavelet defect detection, fast feature extraction (Chen *et al.*, 2009), fabric defects detection using neural network (Mursalin *et al.*, 2008), defect detection in tiles using statistical features (Ghazini *et al.* 2009), texture defect detection (Sobral, 2005), identifying fruit defects using gabor filter (Alimohamdi and Ahmady, 2009), textured materials defect detection (Kumar and Pang, 2002), garments defect detection (Yin and Yu, 2008), patterened defect detection (Ngan *et al.*, 2005), segmentation from ultra sound images (Xie *et al.*, 2005), fast feature extraction (Chen *et al.*, 2009), defect detection using wavelets (Serdaroglu *et al.*, 2006; Han and Shi, 2007; Ngan *et al.*, 2005), inspecting CT images (Li *et al.*, 1996), defect detection using gabor filters (Kumar and Pang, 2002). Most of algorithms are based mainly on two broad categories either spatial or frequency based. Here, researchers have introduced a new algorithm which operates on both frequency and spatial domain. Many algorithms for defect detection uses traditional feature extraction techniques and complicated texture measurement techniques which leads to computational burden.

In this algorithm, gray level image is subjected to feature extraction such as average intensity and a threshold in maximum intensity. If the average intensity is less than the threshold the image is subjected to wavelet transformation. The process is repeated until the average intensity is equal to threshold. At this point, the appropriate wavelet approximation image is selected for further processing. This is done to eliminate the majority of the texture background. This approximation is processed for intensity homogeneity and then the image is checked for sudden intensity variation. The defects will be identified based on homogeneity of pixels and intensity variation.

DETAILED DESIGN

The source gray level image is subjected for feature extraction and then multi scale wavelet transform is performed (Fig. 1).

The multi scale wavelet transform is performed when criteria are met and appropriate wavelet approximation is selected at a point where the criteria is not met. Then, the selected approximation image subjected to check of local homogeneity of pixels. Then, the same image the sudden intensity variation is checked and appropriate processing is done. Then, based on the local homogeneity and intensity variations the defected area is identified.

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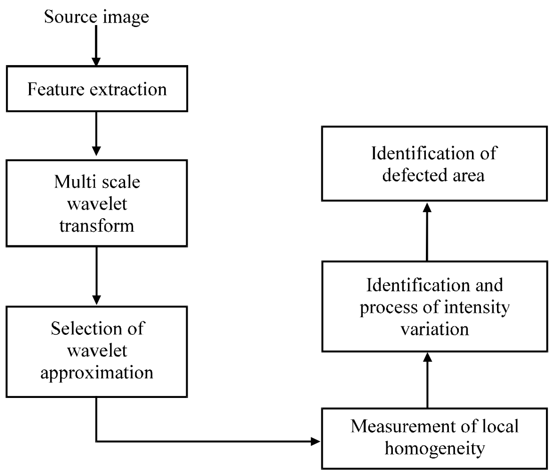

Fig. 1: Detailed architecture of algorithm

FEATURE EXTRACTION AND SELECTION OF APPROPRIATE WAVELET APPROXIMATION

The gray level textile fabric image is subjected to feature extraction. The features such as average intensity and the maximum intensity are obtained. The threshold level is fixed at the 90% of the maximum intensity level of the image. The criteria is set as when the average is less than the threshold then multi scale wavelet analysis is performed. This process is repeated until a wavelet approximation image is obtained. The original signal is applied for wavelet analysis:

$$f(t)=\sum W_{a,b}\psi_{a,b}(x) \tag{1}$$

Equation 1 represents the signal f(t) is obtained by multiplying each coefficient with the scaled and shifted versions of wavelet (Fig. 2).

The multi scale wavelet analysis decomposes the original signal as approximation subimage which consist of low frequency components, detail subimage representing high frequency components such as horizontal subimage, diagonal subimage and vertical subimage. Each time the approximation subimage is subjected to wavelet decomposition when the criteria is met:

$$A_n=\sum cA_n\,\psi_{n,b}(x) \tag{2}$$

$$H_n=\sum cH_n\,\psi_{n,b}(x) \tag{3}$$

$$V_n=\sum cV_n\,\psi_{n,b}(x) \tag{4}$$

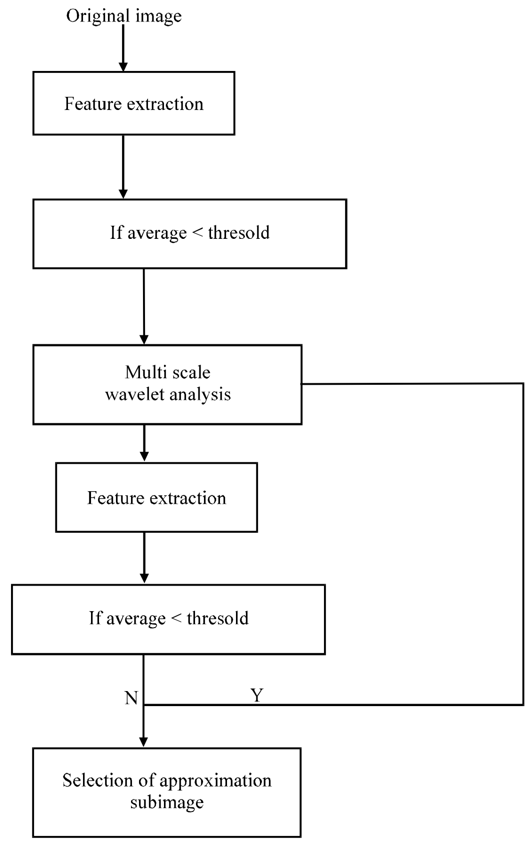

Fig. 2: Detailed description of selection of approximation subimage

$$D_n=\sum cD_n\,\psi_{n,b}(x) \tag{5}$$

Equation 2-5 represent Approximation subimage (An), Horizontal subimage (Hn) and Vertical subimage (Vn), Diagonal subimage (Dn). When threshold is greater than the average value of the approximation then the subimage further subjected to multi scale wavelet analysis if the average is equal or greater than threshold then the appropriate approximation subimage is selected.

IDENTIFYING THE PIXEL HOMOGENEITY

The homogeneity of the pixels with similar properties are identified by using the concept of local homogeneity. The pixels with similar intensity are made as black and with dissimilar intensities are made white:

$$K(i,j)=\sum\left(K(i,j)-K(i,j+1)\right)^2\times K(i,j) \tag{6}$$
$$i=1...n\ ;\ j=1...m$$

The image K is the selected approximation subimage where the homogeneity of the pixels is measured. The i index ranges from 1 to n and j index ranges from 1 to m.

IDENTIFICATION AND PROCESS OF SUDDEN INTENSITY VARIATION

The processed image is tested for sudden intensity variation and a appropriate processing is done on each pixel if the condition is satisfied. The threshold value is fixed for intensity variation. The intensity variation image I is obtained by:

$$\text{thresold} = X1(i,j) + (i,j)\times 10 \quad (7)$$

$$Y1 = X1(i,j+1) \quad (8)$$

If the threshold is greater than or equal to Y1 then the following equation is applied:

$$I(i,j) = X1(i,j) + (X1(i,j)\text{-}X1(i,j+1)) \quad (9)$$

If the threshold is less than Y1 then the following equation is applied:

$$I(i,j+1) = X1(i,j+1) + (X1(i,j)\text{-}X1(i,j+1)) \quad (10)$$

Then, the image I is subjected for edge detection using sobel edge detector.

MORPHOLOGICAL ANALYSIS METHOD

The defect detection in textiles using morphological analysis was proposed by Alimohamadi *et al*. (2009). First the image is subjected to gabor filter with various scales and orientations. The 2D gabor filter has the form such as

$$\psi(x,y) = \frac{1}{2\Pi\partial x\partial y}\exp\left[-\frac{1}{2}\left(\frac{x^2}{\partial_x^2}+\frac{y^2}{\partial_y^2}\right)\right].\exp(j2\Pi Wx) \quad (11)$$

Then, a Gabor wavelet filter is obtained using the equation:

$$\psi_{mn}(x,y) = a^{-m}\psi(x,y) \quad (12)$$

In the above equation, m and n are scale and orientations which varies form m = 1, 2, ..., M-1 and n = 1, 2,..., N-1. The image T(x, y) is Gabor wavelet transformation function is obtained using:

$$G_{mn}^{T}(x,y) = \sum\sum T(x-s, y-t)\psi_{mn}^{*} \quad (13)$$

The mean and standard variance are used to identify the optimal Gabor filter (Kumar and Pang, 2002). The mean is given by the equation:

$$\mu_{mn}^{T} = \frac{\sum\sum\left|G_{mn}^{T}(x,y)\right|}{M\times N} \quad (14)$$

The standard variance is obtained by the equation:

$$\sigma_{mn}^{T} = \frac{\sum\sum\left|G_{mn}^{T}\text{-}\mu_{mn}^{T}\right|}{M\times N} \quad (15)$$

The optimal criterion for Gabor filter is obtained by:

$$F_{mn}^{T} = \frac{\mu_{mn}^{T}}{\sigma_{mn}^{T}} \quad (16)$$

The optimal gabor filter is identified as:

$$\text{Optimum} = \text{Max}\ (F_{mn}^{T})$$

After the optimal gabor filter is chosen the image is subjected to morphological analysis and normalized image is obtained. The normalized image is obtained by:

$$N(x, y) = |M\text{-}T(x, y)| \quad (17)$$

where, M is the average of image T(x, y). After the normalized image is obtained the image is subjected for image reconstruction using a marker and mask. Extraction of regional maximum and domes extraction is used to segregate the defects in textile.

In Fig. 3-5a, b are the respective input and output images which are applied in morphological image processing method. The algorithm is considered efficient in detecting the defects in the image.

WAVELET RECONSTRUCTION METHOD

This method was proposed by Shengqi and Jainchang. The image is decomposed with DB wavelet and then reconstructed. The reconstructed image is subjected to morphological analysis for defect detection. As a first step the image is decomposed into subimages using DB wavelet. The decomposition is done with the equation:

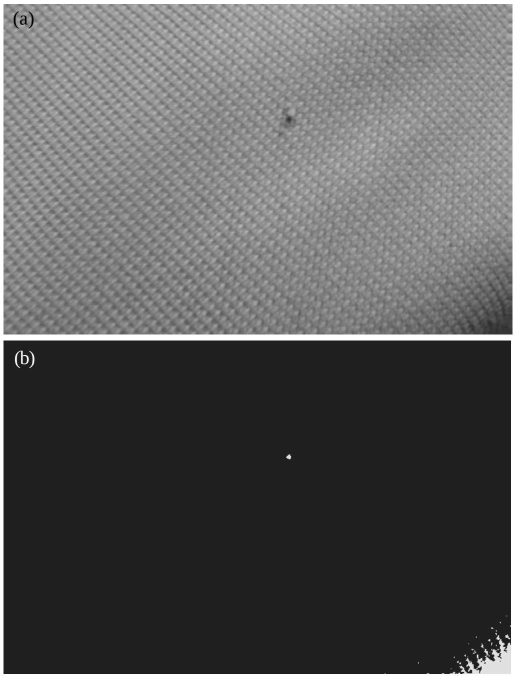

Fig. 3: a) Input and b) Output image

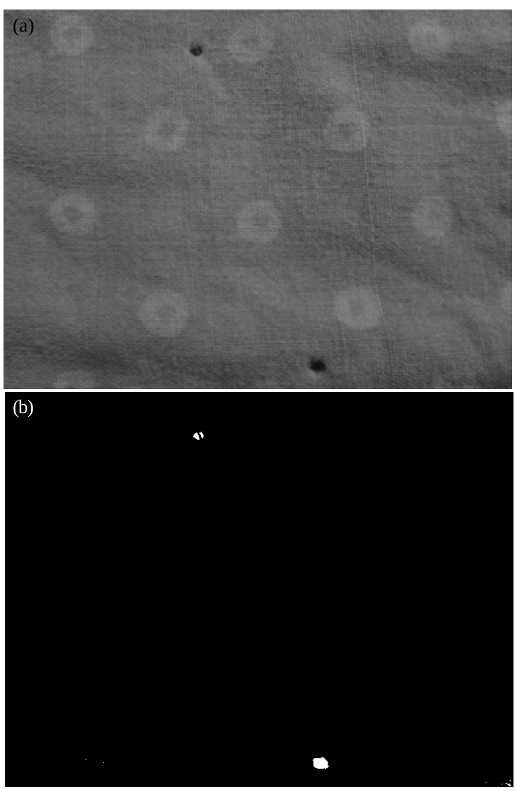

Fig. 4: a) Input and b) Output image

$$c_k^{(j)} = \sum h(2k\text{-}n) c_k^{(j-1)},\ d_k^{(j)} = \sum g(2k\text{-}n) c_k^{(j-1)} \qquad (18)$$

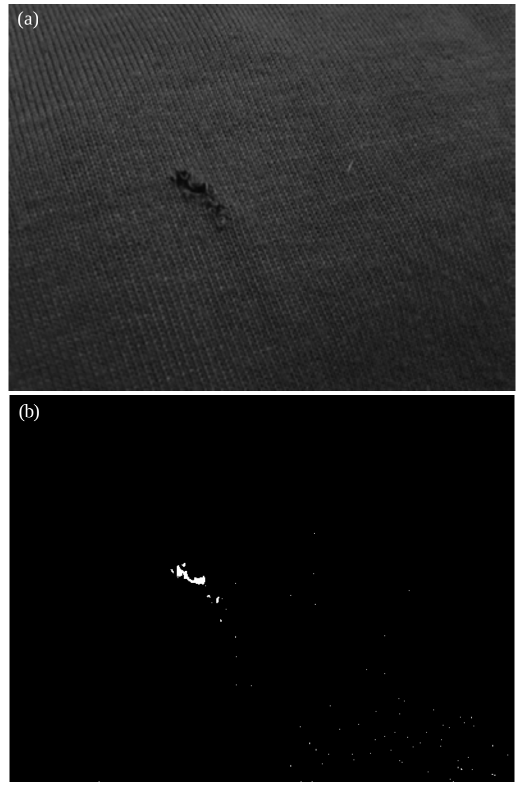

Fig. 5: a) Input and b) Output image

In Eq. 18 n varies from $-\infty$ to ∞. Here, $c_k^{(j)}$ can be seen after low pass filtering and $d_k^{(j)}$ Can be seen after high pass filtering wavelet reconstruction is done with equation such as:

$$c_k^{(j-1)} \sum h(2k\text{-}n) c_k^{(j)} + \sum g(2k\text{-}n) d_k^{(j)} \qquad (19)$$

The wavelet decomposition is done with the help of DB wavelet into sub images. The energy of sub images of wavelet decomposition is expresses as:

$$E = \frac{1}{MXN} \sum \sum \left| f(x, y) \right| \qquad (20)$$

In Eq. 20 f(x, y) is called as gray level of the pixel. The approximation image is selected for reconstruction. Two images are used such as En the sub image and Et the test image. The sub image which has greater energy than the test image is chosen for reconstruction. The reconstructed image is subjected to morphological analysis for defect detection.

Figure 6-8a, b are the original and the segmented result obtained from wavelet reconstruction method.

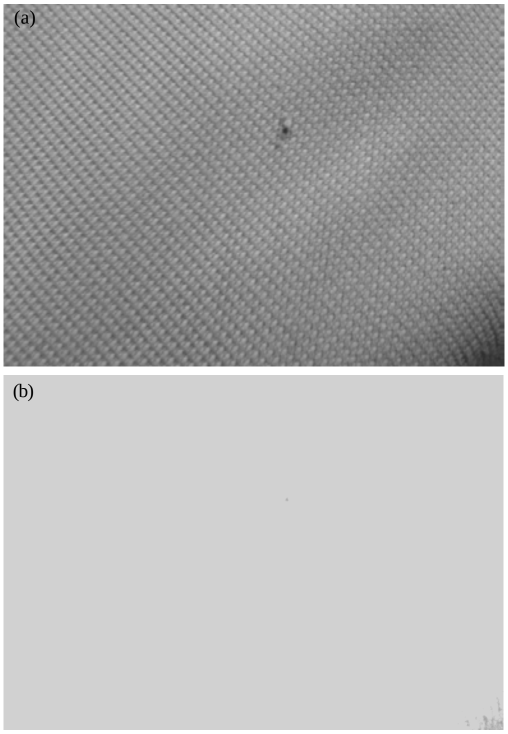

Fig. 6: a) Origional and b) segmental image

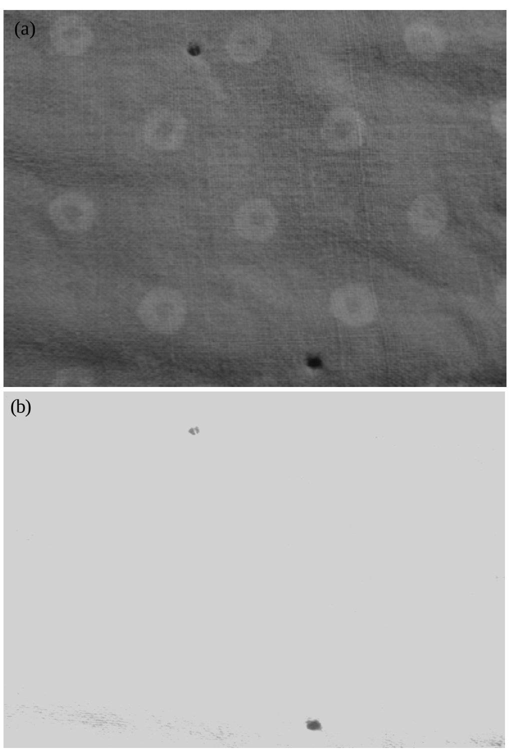

Fig. 7: a) Origional and b) segmental image

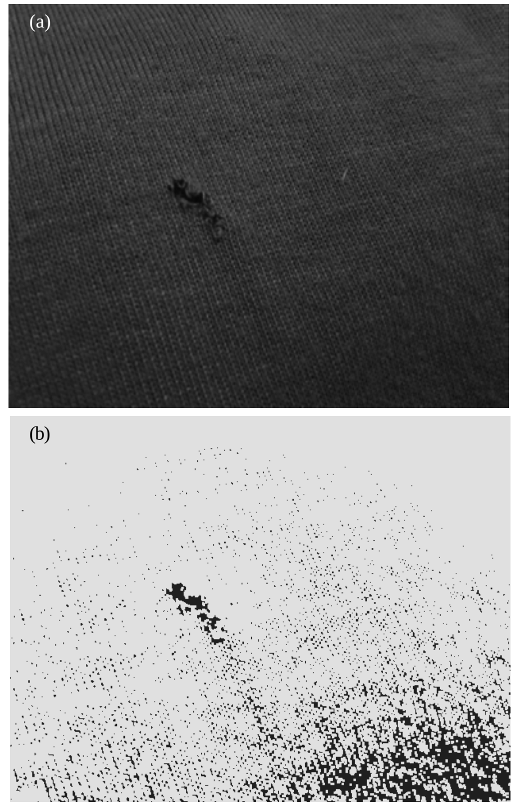

Fig. 8: a) Origional and b) segmental image

Figure 8b shows the defect is detected accurately but it also results in false negatives. False negatives are non defected portions are considered as defects.

EXPERIMENTAL RESULTS

The algorithm is applied for various texture images almost all the images the defected area is identified with minor error rate

Figure 9a-c and 10a-c are the input image, approximation image and the segmented image, respectively. The above images show that the defected areas in the textile fabric has been accurately identified without any false negatives.

ANALYSIS

The proposed algorithm is compared with existing Wavelet Reconstruction Method and Morphological Analysis Method results. Around 50 samples has been tested with the algorithm and it has been proved that it is better in defect detection and speed. The defects has been identified as stains.

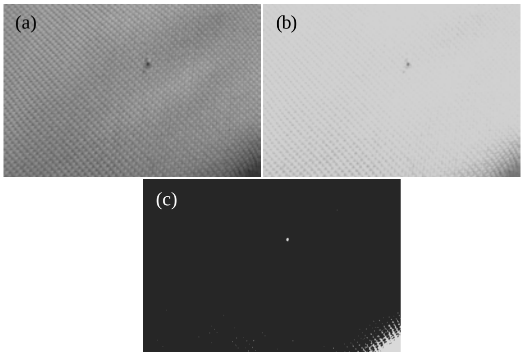

Fig. 9: a) Input; b) aproximation and c) sgmented image

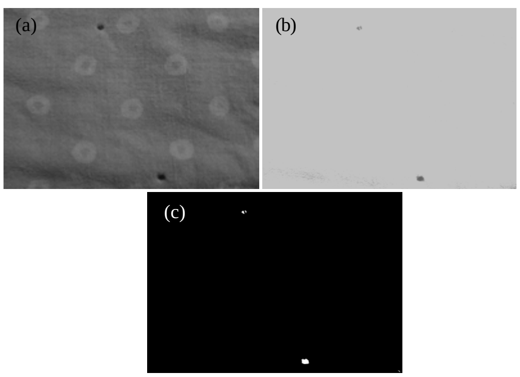

Fig. 10: a) Input; b) aproximation and c) sgmented image

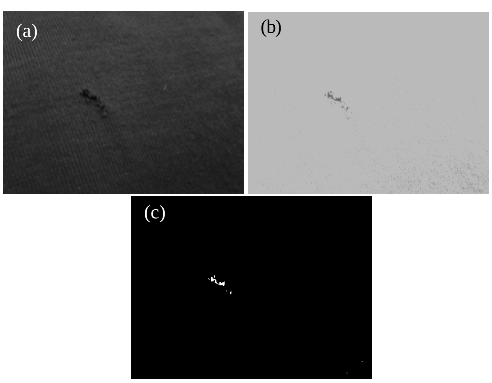

Fig. 11: a) Input; b) approximation and c) segmented image

Table 1: Comparative statistics proposed method versus Wavelet Reconstruction Method

		Proposed algorithm		Wavelet Reconstruction Method	
Image	No. of stains	Stains identified	Speed (sec)	Stains identified	Speed (sec)
Sample 1	2	2	3.6427	1	4.5758
Sample 2	2	2	4.8783	2	4.9014
Sample 3	1	1	4.0383	1	4.5410

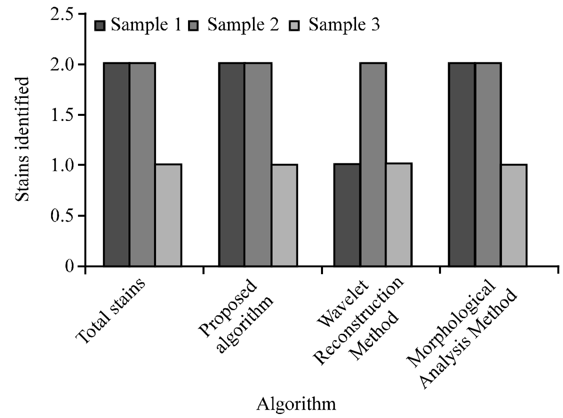

Fig. 12: Pictorial representation of defect detection between algorithms

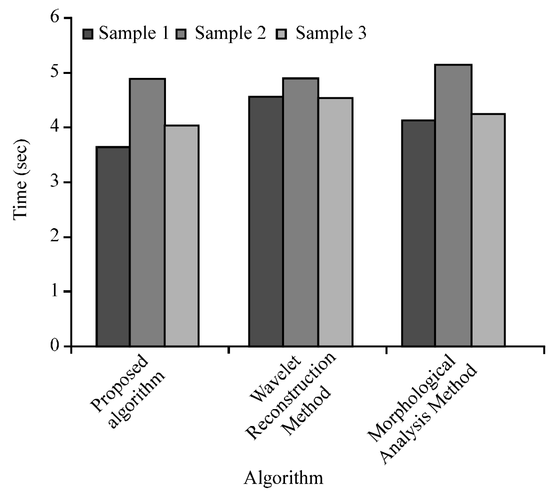

Fig. 13: Pictorial representation of defect detection speed between algorithms

Table 2: Comparative statistics proposed method versus Morphological Analysis Method

		Proposed algorithm		Morphological Analysis Method	
Image	No. of stains	Stains identified	Speed (sec)	Stains identified	Speed (sec)
Sample 1	2	2	3.6427	2	4.1454
Sample 2	2	2	4.8783	2	5.1317
Sample 3	1	1	4.0383	1	4.2267

In Table 1 and 2, Fig. 3, 6 and 9 are classified as sample 1, Fig. 4, 7 and 10 as sample 2 and Fig. 5, 8 and 11 as sample 3. Table 1 reveals the comparative statistics between proposed method and Wavelet Reconstruction Method the results tabulated reveals that proposed method is accurate and approximately 11% faster than wavelet reconstruction method. Table 2 highlights the comparative analysis between proposed method and Morphological Analysis Method. The statistics presented shows both methods are good in accuracy but proposed method is approximately 7% faster than Morphological Analysis Method. Figure 12 shows the graphical representation of accuracy and Fig. 13 shows the speed between the methods deployed.

CONCLUSION

The above algorithm is a new algorithm which uses purely non texture methods for texture defect detection. It is also, a algorithm which operates on both frequency and spatial domains. The above algorithm is successful in 90% of high texture background images. However, it is limited to detection of discontinuities and stains in low texture background images. More research has to be done on defects of various origins.

REFERENCES

Alimohamadi, H., A. Ahmadyfard and E. Shojaee, 2009. Defect detection in textiles using morphological analysis of optical gabor wavelet filter response. Proceedings of the International Conference on Computer and Automation Engineering, March 8-10, 2009, Bangkok, pp: 26-30.

Alimohamdi, H. and A. Ahmady, 2009. Detecting skin defect of fruits using optimal Gabor wavelet filter. Proceedings of the International Conference on Digital Image Processing, March 7-9, 2009, Bangkok, pp: 402-406.

Bhalerao, A. and R. Wilson, 2001. Unsupervised image segmentation combining region and boundary estimation. Image Vision Comput., 19: 353-368.

Chen, Y.L., T.W. Chen and S.Y. Chien, 2009. Fast texture feature extraction method based on segmentation for image retrieval. Proceedings of the 13th International Symposium on Consumer Electronics, May 25-28, 2009, Kyoto, pp: 941-942.

Ghazini, M., S.A. Monadjemi, N. Movahhedinia and K. Jamshidi, 2009. Defect detection of tiles using 2D wavelet transform and statistical features. World Acad. Sci. Eng. Technol., 49: 901-904.

Han, Y. and P. Shi, 2007. A adaptive level-selecting wavelet transform for texture defect detection. Image Vision Comput., 25: 1239-1248.

Kumar, A. and G.H.K. Pang, 2002. Defect detection in texture materials using gabor filters. IEEE Trans. Industry Applic., 38: 425-440.

Li, P., A.L. Abbott and D.L. Schmoldt, 1996. Automated analysis of CT images for the inspection of hardwood logs. Proceedings of the International Conference on Neural Networks, Volume 3, June 2-6, 1996, Washington, DC., pp: 1744-1749.

Mursalin, T.E., F.Z. Eishita and A.R. Islam, 2008. Fabric defect inspection system using neural network and microcontroller. J. Theoretical Applied Informat. Technol., 4: 560-570.

Ngan, H.Y.T., G.K.H. Pang, S.P. Yung and M.K. Ng, 2005. Wavelet based methods on patterened fabric defect detection. Pattern Recognit., 38: 559-576.

Serdaroglu, A., A. Ertuzun and A. Ercil, 2006. Defect detection in textile fabric images using wavelet transforms and independent component analysis. Pattern Recognit. Image Anal., 16: 61-64.

Sobral, J.L., 2005. Optimized filters for texture defect detection. Proceedings of the International Conference on Image Processing, Volume 3, September 11-14, 2005, Genoa, Italy, pp: 565-568.

Xie, J., Y. Jiang and H.T. Tsai, 2005. Segmentation of kidney from ultra sound images based on texture and shape priors. Trans. Med. Imaging, 24: 45-57.

Yin, K. and W. Yu, 2008. Image processing for the use of garment production detection system. Proceedings of the Congress on Image and Signal Processing, Volume 3, May 27-30, 2008, Sanya, China, pp: 349-352.