Journal of Engineering and Applied Sciences 9 (2): 43-49, 2014
ISSN: 1816-949X

Defect Detection Algorithm for Gray Level Digital Images Using Local Homogeneity and Discrete Cosine Transform

Ali Rebhi, Sabeur Abid and Farhat Fnaeich
Scientific Research Laboratory in Signal, Image Processing and Energy Mastery: SIME,
University of Tunis, 5 Av. Taha Hussein, 1008 Tunis, Tunisia

Abstract: In industrial field, the automated visual inspection systems is applied effectively to identify the defects in various digital images. In this research work researchers have proposed a new defect detection algorithm based on local homogeneity and Discrete Cosine Transform (DCT) to eliminate the texture elements in the digital image by isolating the defected area. Firstly, the local homogeneity of each pixel is computed to construct a new Homogeneity image denoted as (H-image). Then a DCT transform in order to extract features energy is applied. After these energy are integrated by the Hotelling's T^2 statistic and the defect blocks can be determined by the multivariate statistical method. Finally, a simple thresholding method is applied to set a threshold for distinguishing between defective areas and uniform regions. Simulations on different textured images show good promising results. This new automatic defect detection method shows good performance in comparison with other existing algorithms.

Key words: Defect detection, textured image, local homogeneity (H-image), Discrete Cosine Transform (DCT), energy

INTRODUCTION

Defect detection becomes a very important task in quality control. Manual inspection imposes limitations on identifying defects in term of accuracy, consistency and efficiency. For this reason, manual inspection systems have been replaced by automated visual inspection systems. The automated visual inspection systems are used in many industrial and commercial applications. There are various visual inspection systems, such as defect detection of tiles (Ghazvini *et al*., 2009; Conners *et al*., 1983; Zhu *et al*., 1991) ceramic (Boukouvalas *et al*., 1999), sheet steel (Wiltschi *et al*., 2000), textiles (Kumar, 2003; Chetverikov, 2000) and etc.

Textures analysis are of a great interest in image processing and there are many applications in their analyzing and processing, one of which is defect detection. Some researchers are interested in identifying low-contrast defects in unevenly illuminated images in order to help the manufacturers finding Mura (Mura is one large category of defects found in LCD manufacturing) defects in Liquid Crystal Display (LCD) panels (Li and Tsai, 2011). It is for them of prime importance to detect any defect in the patterns they get in order to avoid economic losses. Textures analysis are also needed in mechanical engineering where one wants to find a welding defect (Mhamed *et al*., 2012; Hassan *et al*., 2012).

In this study, researchers are interested in textures defects detections. These applications have been an intense research area in recent years. However, it seems that all of the proposed approaches suffer of many drawbacks. Therefore, researchers introduce a novel method for texture defect detection which is based on local homogeneity and Discrete Cosine Transform (DCT). The major advantage of the method is the high and strong accuracy of detection of the defects in the areas characterized by a weak variation in gray level.

Problem statement and related research: Before researchers introduce the methods researchers want to first introduce the problem researchers are aiming to solve and then explain how the known methods will fail at this task.

Problem statement: In this research, the objective is to solve the following problem: Given a textured images that contains a defects, researchers will want to determine the location of the latter. The problem declared is independent of the types of defect that can happen. Researchers are interested to fabrics defect detection.

Corresponding Author: Ali Rebhi, Scientific Research Laboratory in Signal, Image Processing and Energy Mastery: SIME, University of Tunis, 5 Av. Taha Hussein, 1008 Tunis, Tunisia

Related research: According to recent surveys, the different methods for texture defect detection can be broadly categorized into 3 classes: Statistical, spectral and model based. Statistical approaches were the earliest approaches used to detect fabric defects. Many statistical detection methods were reported in the literature, including edge detection (Conci and Proenca, 2000), cross-correlation (Bodnarova *et al*., 1998), co-occurrence matrix (Siew *et al*., 1988; Latif-Amet *et al*., 2000) and neural networks (Kumar, 2003). The statistical approaches can be divided into first order, second order and higher order levels. Several first order statistics are used (Ramana and Ramamoorthy, 1996), such as variance, skewness and kurtosis from the gray-level histogram of an image. The second-order statistical method includes the gray level co-occurrence matrix. Siew *et al*. (1988) applied the co-occurrence matrix method to assess carpet wear by using 2 order gray level statistics to build up probability density functions of intensity changes. Also Latif-Amet *et al*. (2000) proposed wavelet theory and co-occurrence matrix for detection of defects encountered in textile images and classify each sub-window as defective or non-defective with a Mahalanobis distance.

Moreover, model based approaches have been successfully used in fabric defect detection. Some of textural analysis methods are based on the Markov random field model (Ozdemir and Ercil, 1996). Campbell *et al*. (1997) used the model based clustering method to detect linear pattern production defects.

The spectral approaches constitute the largest number of fabric defect detection methods proposed in the literature. These approaches includes 3 techniques: Fourier transform (Chan and Pang, 2000; Campbell and Murtagh, 1998), wavelet transform (Tsai and Hsiao, 2001; Wong *et al*., 2009; Ghazvini *et al*., 2009) and Gabor filter (Mak and Peng, 2008; Chen *et al*., 2010; Zhang *et al*., 2010). An approach based on Fourier transform has been described by Chan and Pang, (2000) to detect the structural defect in fabric. In Campbell and Murtagh (1998), a WFT based method to detect defects on denim fabric was detailed. WFT with a 16×16 pixels window were used to extract amplitude spectrum features.

The wavelet transform has been extensively studied in this field. The multiresolution wavelet representation allows an image to be decomposed into a hierarchy of localized sub images at different spatial frequencies. In Tsai and Hsiao (2001) proposed a multi-resolution approach for inspecting local defects embedded in homogeneous textured surfaces. By properly selecting the smooth sub-image or the combination of detail sub-images in different decomposition levels for backward wavelet transform, regular, repetitive texture patterns can be removed and only local anomalies are enhanced in the reconstructed image.

The Gabor filtering technique has been applied to fabric defects detection. This technique shows a strong dependence on certain number of parameters. Chen *et al*. (2010) proposed a method of fabric defects detection using Gabor filter based on scale transformation. There is a key to choose the parameter for threshold processing. If the parameter is too small, defects will be confused with normal fabric texture, if too big, defects will be ignored.

In recent years, other methods have been developed for texture defect detection while combining the statistical and spectral approaches. Lin (2007) proposed an approach for visual inspection of ripple defects. This approach used wavelet decomposition to extract feature vectors to describe the surface properties. Then, multivariate statistics of Hotelling T^2 control chart were applied to integrate the multiple texture features and judge the existence of ripple defects in the image.

TEXTURE DEFECT DETECTION

Local homogeneity computation: It is known that dscontinuities in textured images represent generally an important feature such as boundaries. The main problem is how to detect these discontinuities? A method to resolve this problem is the Homogeneity (H). The calculation of H was proposed first by Yang *et al*. (2010). Let (x, y) be coordinates of a pixel and I (x, y) the corresponding intensity level. Let P be a squared window, i.e., a mask of (2N+1) width centered on the pixel I_c (x_c, y_c). In the window P1 can define different vectors, such as: $Cp_i = (x_i-x_c, y_i-y_c)$ where (x_i, y_i) is the neighbor of the center (x_c, y_c) defined as:

$$\begin{Bmatrix} c-N \le x_i \le c+N \\ c-N \le y_i \le c+N \end{Bmatrix} \tag{1}$$

This definition allows to compute the homogeneity of a pixel for different mask sizes (3×3), (5×5), etc. Figure 1 shows an example of the different pixels used to compute homogeneity in a window of size (3×3) pixels. Based on Cp_i a new vector f_i is constructed as follows:

$$f_i = \left(I(x_i, y_i) - I(x_c, y_c)\right)\frac{Cp_i}{\|Cp_i\|} \tag{2}$$

For a mask of width (2N+1) researchers have $(2N+1)^2$ vectors f_i: $1 \le i \le (2N+1)^2$. Let f be the sum of the whole vectors defined in the window P, so:

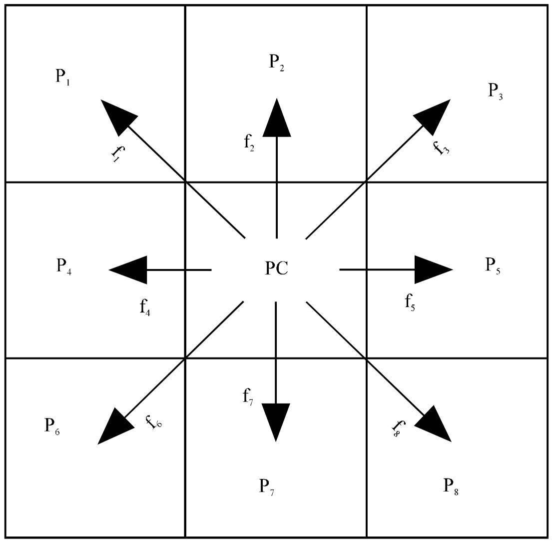

Fig. 1: Different vectors fi used to compute the local homogeneity for 3×3 masks

$$f = \sum_{i=1}^{(2N+1)^2} f_i \tag{3}$$

The H value measurement (the homogeneity value) is defined as the norm of f, so that:

$$H = \|f\| \tag{4}$$

To limit the huge variation of the local homogeneity, the normalized homogeneity is used:

$$\hat{H} = \frac{H - H_{min}}{H_{max} - H_{min}} \tag{5}$$

The resulting H-image is constructed by the different values of $\hat{H}$ computed for each pixel value I_c (x_c, y_c). The resulting H-image is a gray-scale one whose pixel values are the values of the pixel homogeneities. It is easily noted that the $\hat{H}$ values are very small for homogenous regions and high within boundaries and non homogenous regions. Consequently, the H-image can be viewed as a transformation of the original one where the homogenous regions are transformed on dark areas and the non homogenous region on gray scale regions. It follows that the H-image can be used as a discontinuity measures in an image.

Discrete cosine transform: The Discrete Cosine Transform (DCT) is one of the extensive family of sinusoidal transform. The concept of this transformation is to transform as set of points from the spatial domain into an identical representation in frequency domain. The DCT of an H-image $H_{x,y}$ of size (M×N) is given by the Eq. 6. This expression must be computed for values of u = 0, 1, 2, ..., M-1 and also for v = 0, 1, 2, ..., N-1.

$$D_{u,v} = \sigma(u)\sigma(v)\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} H_{x,y}\cos\left(\frac{(2x+1)u\pi}{2M}\right)\cos\left(\frac{(2y+1)v\pi}{2N}\right) \tag{6}$$

Where:

$$\sigma(u) = \begin{cases} \sqrt{1/M}, & \text{for } u = 0 \\ \sqrt{2/M}, & \text{otherwise} \end{cases} \tag{7}$$

$$\sigma(v) = \begin{cases} \sqrt{1/N}, & \text{for } v = 0 \\ \sqrt{2/N}, & \text{otherwise} \end{cases} \tag{8}$$

Where:
u and v = Frequency variables
x and y = Spatial variables
P and Q = The size of the DCT block

A lot of energy concentrates in the origin (u = 0, v = 0) and that the energy decreases gradually from the origin and the low frequency zone on the top-left side to the high frequency zone on the bottom-right side. The 5 energies can be extracted from the DCT transform are expressed as follows:

$$E_H = \sum_{u=0}^{M-1}\sum_{v=0}^{N-1}\left[(v+1)^2 \times H^2{}_{x,y}\right]^{1/2}, \text{ for } u+v \neq 0 \tag{9}$$

$$E_V = \sum_{u=0}^{M-1}\sum_{v=0}^{N-1}\left[(u+1)^2 \times H^2{}_{x,y}\right]^{1/2}, \text{ for } u+v \neq 0 \tag{10}$$

$$E_D = \sum_{u=0}^{M-1}\sum_{v=0}^{N-1}\left[(u+1)\times(v+1)\times H^2{}_{x,y}\right]^{1/2}, \text{ for } u+v \neq 0 \tag{11}$$

$$E_M = \frac{1}{M\times N}\sum_{u=0}^{M-1}\sum_{v=0}^{N-1} H^2{}_{x,y} \tag{12}$$

$$E_S = \frac{1}{M\times N-1}\sum_{u=0}^{M-1}\sum_{v=0}^{N-1}(H_{x,y} - E_M)^2 \tag{13}$$

Where:
E_H = The horizontal energy value of a DCT block
E_V = The vertical energy value of a DCT block

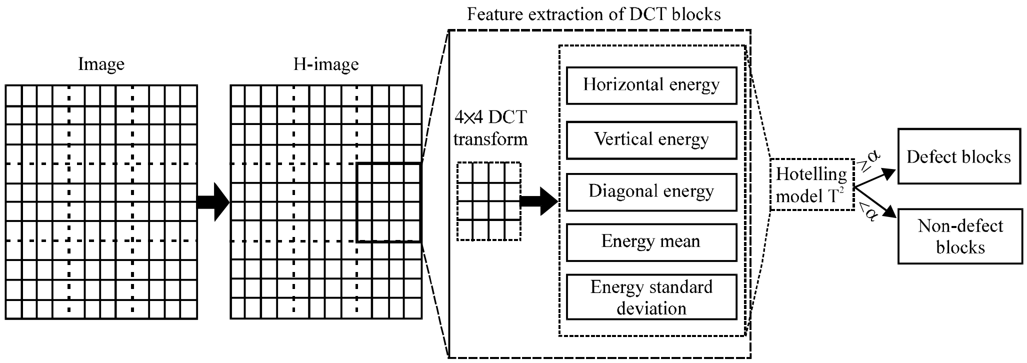

Fig. 2: Concept diagram of the proposed methods

E_D = The diagonal energy value of a DCT block
E_M = Average energy value of a DCT block
E_S = The standard deviation of energy value of a DCT block

Proposed algorithm: This method consists in scanning the original image with a squared window and computing the local homogeneity for each pixel and constructing the (H-image). In the research, researchers have used a window of size (11×11) pixels. After, divide the H-image into squared blocks. The application of DCT transform for each blocks that produces 5 energy. These energy are the origin of the calculation of the Hotelling model T^2. After that the Hotelling T^2 is compared to a threshold that is calculated using Mahalanobis distance. If T^2 exceeds the threshold, the block is assumed to be containing defect, else it does not present any anomaly. Figure 2 shows the concept diagram of the proposed method. The defect localization algorithm can be described by the following steps: For an image I of the size (M×N) pixels.

- In step 1; scan the input image I with a squared window and compute the local homogeneity for each pixel and construct the (H-image)
- In step 2; divide the H-image into squared blocks
- In step 3; applied the DCT transform of each blocks
- In step 4; compute the 5 energy feature of a DCT blocks
- In step 5; calculate the mean vector of each blocks

$$\overline{X_i} = \begin{bmatrix} \overline{X1} \\ \overline{X2} \\ \overline{X3} \\ \overline{X4} \\ \overline{X5} \end{bmatrix} = \begin{bmatrix} \log_{10} \overline{E_H} \\ \log_{10} \overline{E_D} \\ \log_{10} \overline{E_V} \\ \log_{10} \overline{E_M} \\ \log_{10} \overline{E_S} \end{bmatrix} \tag{14}$$

- In step 6; calculate the covariance matrix S:

$$S = \begin{bmatrix} S^2_{EH} & S_{E_H E_V} & S_{E_H E_D} & S_{E_H E_M} & S_{E_H E_S} \\ S_{E_H E_V} & S^2_{EV} & S_{E_V E_D} & S_{E_V E_M} & S_{E_V E_S} \\ S_{E_H E_D} & S_{E_V E_D} & S^2_{ED} & S_{E_D E_M} & S_{E_D E_S} \\ S_{E_H E_M} & S_{E_D E_M} & S_{E_M E_D} & S^2_{EM} & S_{E_M E_S} \\ S_{E_H E_S} & S_{E_V E_S} & S_{E_D E_S} & S_{E_M E_S} & S^2_{ES} \end{bmatrix} \tag{15}$$

Where:
s^2_p = The sample variance of the p characteristic of an image
$S_{p,q}$ = The sample covariance of the p and q characteristics of an image

- In step 7; calculate the Hotelling model T^2 of each block

$$T^2 = n\left(X_i - \overline{X_i}\right)^T S^{-1}\left(X_i - \overline{X_i}\right) \tag{16}$$

- In step 8; thresholding If $T^2 > \alpha$ the block contains a defect, else it does not present any anomaly. Where α is a threshold calculated from the Mahalanobis distance

SIMULATION RESULTS

In the purpose of evaluating the performance of the proposed method, researchers shall present experimental results on a variety textured images and defects. The algorithm is implemented on a personal computer (Intel® core™ 2Duo CPU T5870 @2Gh) using the Matlab language. The proposed method was tested on textured images from Brodatz album. Several images with various defect types were used to test the performance of the proposed new algorithm.

Performance index for defect detection: In spite of the great number of researches developed in the field of the defect detection, one cannot find a standard criterion for evaluating the performance of a defect detection algorithm. This is due to the big variety of images and defects in form, intensity, distribution and the number of existing defects in one image, etc.

In literature several attempt are made for this purpose. In Ghazvini *et al.* (2009), Ngan *et al.* (2010), researchers used the True Positive (TP) and True Negative (TN) pixels to construct a detection success rate. Table 1 outlines definitions of the True Positive (TP), the False Positive (FP), the True Negative (TN) and the False Negative (FN) in defect detection (Table 1).

Based on these parameters, the detection success rate (known also as detection accuracy) is defined as:

$$\text{Detection success rate} = \frac{TP + TN}{TP + FN + TN + FP} \quad (17)$$

On the other hand, correct detection of defective samples (i.e., sensitivity) and correct detection of defect-free samples (i.e., specificity) can be defined as:

$$\text{Sensitivity} = \frac{TP}{TP + FN} \quad (18)$$

Table 1: Definitions of True Positive (TP), False Positive (FP), True Negative (TN), False Negative (FN) in defect detection

Parametres	Actually defective	Actually defect-free
Detected as defective	True Positive (TP)	False Positive (FP)
Detected as defect-free	False Negative (FN)	True Negative (TN)

$$\text{Specificity} = \frac{TN}{TN + FP} \quad (19)$$

Comparison with other methods: The proposed algorithm is compared with several methods well known literature, such as the method presented by Chiu and Lin (2012) based on DCT transform and the method published in Rebhi *et al.* (2011) based on defect detection using local homogeneity analysis (Fig. 3).

For each method researchers evaluated the sensitivity, the specificity and the percentage in detection success rate. Table 2-4 show a summary of these parameters for each method.

Table 2: Comparison of the sensitivity for different methods

Image number	DCT method (%)	H-image method (%)	Proposed method (%)
1	88.2	84.1	96.3
2	89.6	92.6	95.6
3	93.4	92.6	96.5
4	79.2	83.5	97.8

Table 3: Comparison of the specificity for different methods

Image number	DCT method (%)	H-image method (%)	Proposed method (%)
1	87.8	79.3	96.8
2	89.6	85.9	97.3
3	91.3	90.5	94.53
4	73.9	82.3	95.3

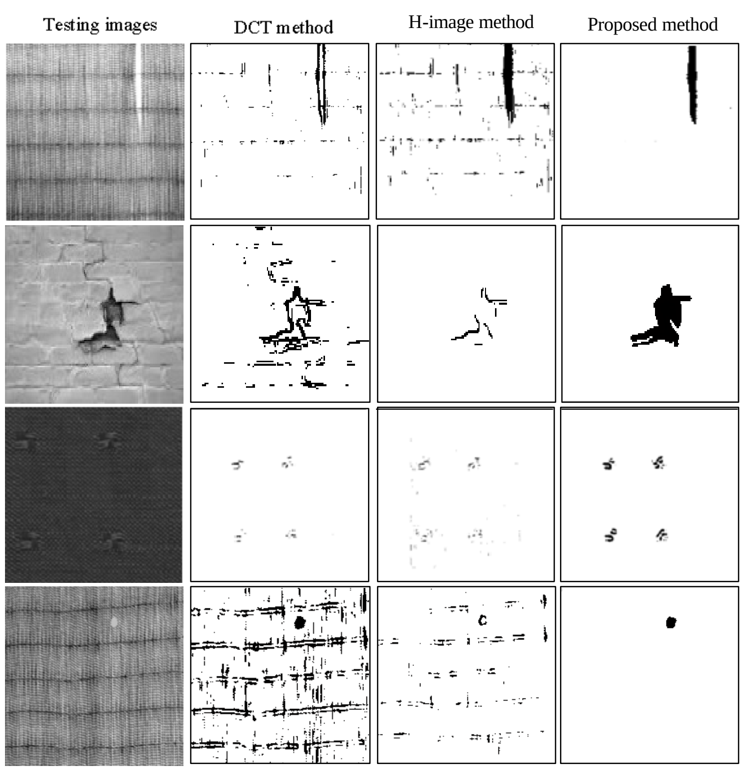

Fig. 3: Defect detection results using DCT, H-image and the proposed methods

Table 4: Comparison of the detection success rate for different methods

Image number	DCT method (%)	H-image method (%)	Proposed method (%)
1	92.12	90.91	96.1
2	89.6	85.9	97.3
3	91.3	89.45	96.4
4	79.2	83.5	97.8

From these results, researchers note that the proposed algorithm based on based on feature extraction from DCT transform of the H-image overcome the other method in terms of the sensitivity, specificity percentage in the detection success rate.

CONCLUSION

In this study, a new algorithm for defect detection in textured images is proposed. It is based on feature extraction from DCT transform of the H-image. This later can be obtained from the local homogeneity of each pixel. The proposed approaches use the multivariate statistics of Hotelling T^2 and Mahalanobis distance to judge the existence of texture defect. Simulation results have shown that the proposed algorithm can effectively detect the existence of the defects when exist. Moreover, the research can easily be extended for color images by applying the different algorithm steps on the RGB image components.

REFERENCES

Bodnarova, A., M. Bennamoun and K.K. Kubik, 1998. Defect detection in textile materials based on aspects of HVS. Proceedings of the IEEE International Conference on Systems, Man and Cybernetics, October 11-14, 1998, San Diego, CA., pp: 4423-4428.

Boukouvalas, C., J. Kittler, R. Marik and M. Petrou, 1999. Color grading of randomly textured ceramic tiles using color histogram. IEEE Trans. Ind. Electron., 46: 219-226.

Campbell, J.G., C. Fraley, F. Murtagh and A.E. Raftery, 1997. Linear flaw detection in woven textiles using model-based clustering. Pattern Recogn. Lett., 18: 1539-1548.

Campbell, J.G. and F.D. Murtagh, 1998. Automatic visual inspection of woven textiles using a two-stage defect detector. Opt. Eng., 37: 2536-2542.

Chan, C.H. and G.K.H. Pang, 2000. Fabric defect detection by Fourier analysis. IEEE Trans. Ind. Appl., 36: 1267-1276.

Chen, S., J. Feng and L. Zou, 2010. Study of fabric defects detection through gabor filter based on scale transformation. Proceedings International Conference on Image Analysis and Signal Processing, April 9-11, 2010, Zhejiang, pp: 97-99.

Chetverikov, D., 2000. Structural defects: General approach and application to textile inspection. Proceeding 15th International Conference Pattern Recognition, 2000, Barcelona, pp: 521-524.

Chiu, Y.S. and H.D. Lin, 2012. An innovative blemish detection system for curved LED lenses. Expert Syst. Appl., 40: 471-479.

Conci, A. and C.B. Proenca, 2000. A computer vision approach for textile inspection. Text. Res. J., 70: 347-350.

Conners, R.W., C.W. McMillin, K. Lin and R.E. Vasquez-Espinosa, 1983. Identifying and locating surface defects in wood: Part of an automated lumber processing system. IEEE Trans. Patt. Anal. Machine Intell., 6: 573-583.

Ghazvini, 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.

Hassan, J., A.M. Awan and A. Jalil, 2012. Welding defect detection and classification using geometric features. Proceedings of the 10th International Conference on Frontiers of Information Technology, December 17-19, 2012, Islamabad, Pakistan, pp: 139-144.

Kumar, A., 2003. Neural network based detection of local textile defects. Pattern Recognit., 36: 1645-1659.

Latif-Amet, L., A. Ertuzun and A. Ercil, 2000. An efficient method for texture defect detection: Subband domain co-occurrence matrices. Image Vision Comput., 18: 543-553.

Li, W.C. and D.M. Tsai, 2011. Defect inspection in low-contrast lcd images using hough transform-based nonstationary line detection. IEEE Trans. Ind. Inform., 7: 136-147.

Lin, H.D., 2007. Automated visual inspection of ripple defects using wavelet characteristic based multivariate statistical approach. Image Vis. Comput., 25: 1785-1801.

Mak, K.L. and P. Peng, 2008. An automated inspection system for textile fabrics based on Gabor ?lters. Robot. Comput. Integr. Manuf., 24: 359-369.

Mhamed, I.B., S. Abid and F. Fnaiech, 2012. Weld defect detection using a modified anisotropic diffusion model. EURASIP J. Adv. Signal Process., Vol., 46. 10.1186/1687-6180-2012-46

Ngan, H.Y.T., G.K.H. Pang and N.H.C. Yung, 2010. Performance evaluation for motif-based patterned texture defect detection. IEEE Trans. Automat. Sci. Eng., 7: 58-72.

Ozdemir, S. and A. Ercil, 1996. Markov random ?elds and Karhunen-Loeve transforms for defect inspection of textile products. Proceedings of the IEEE Conference on Emerging Technologies and Factory Automation, November 18-21, 1996, Kauai, HI., pp: 697-703.

Ramana, K.V. and B. Ramamoorthy, 1996. Statistical methods to compare the texture features of machined surfaces. Pattern Recognit., 29: 1447-1459.

Rebhi, A., S. Abid and F. Fnaiech, 2011. Texture defect detection using local homogeneity analysis. Proceedings of the 11th Mediterranean Microwave Symposium, September 8-10, 2011, Yasmine Hammamet, Tunisia -.

Siew, L.H., R.M. Hodgson and E.J. Wood, 1988. Texture measures for carpet wear assessment. IEEE Trans. Pattern Anal. Mach. Intell., 10: 92-150.

Tsai, D.M. and B. Hsiao, 2001. Automatic surface inspection using wavelet reconstruction. Pattern Recognit., 34: 1285-1305.

Wiltschi, K., A. Pinz and T. Lindeberg, 2000. An automatic assessment scheme for steel quality inspection. Extended Vers. Mach. Vis. Appl., 12: 113-128.

Wong, W.K., C.W.M. Yuen, D.D. Fan, L.K. Chan and E.H.K. Fung, 2009. Stitching defect detection and classification using wavelet transform and BP neural network. Expert Syst. Appl., 36: 3845-3856.

Yang, Q., J.S. Zhang and X.F. Huang, 2010. Adaptive image enhancement algorithm combining kernel regression and local homogeneity. Math. Probl. Eng. 10.1155/2010/693532

Zhang, Y.H., C.W.M. Yuen and W.K. Wong, 2010. A new intelligent fabric defect detection and classification system based on gabor filter and modified elman neural network. Proceedings of the IEEE International Conference Advance Computer Control, March 27-29, 2010, Shenyang, pp: 652-656.

Zhu, D.P., R.W. Conners and P. Araman, 1991. CT image sequence processing for wood defect recognition. Proceedings of the 23rd Southeastern Symposium on System Theory, March 10-12, 1991, Columbia, SC., pp: 75-79.