

Fully Automated Fabric Defect Detection Using Additive Wavelet Transform

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Abstract—This paper introduces a proposed fabric defect detection technique based on additive wavelet transform. In this paper, à trous wavelet is utilized to extract the approximate sub image at an appropriate level. The objective of the proposed technique is to enhance energy of defective region and attenuate energy of background in the selected level. An improved thresholding method based on statistical calculation is used.

1. Introduction

Textile defect detection is one of the most important procedures that effects quality level in fabric industry. Human visual inspection produces high error rate, low efficiency, and high cost. Automated visual inspection [1] gives higher quality of products in the production line. Fabric defect detection has two categories patterned and unpatterned fabrics. In the literature fabric defect detection algorithms mostly concentrate on un patterned fabric. They used structural, statistical, spectral, and model based learning for these researches. Algorithms for defect detection in patterned fabric were developed by using combination of computational methods [1,2].

A statistical approach name co-ocurrence matrix was used to characterize texture features as a second order statistics tool by measuring 2D spatial dependence of gray values [3]. This method has poor performance in texture patterns due to large computational complexity. Fourier based methods characterize the image in spatial domain but they can remove line patterns in the inverse Fourier transform as well as periodic and repetitive patterns of any statistical structure [4]. Gabor filter achieved optimal joint resolution in spatial and frequency domain . Basically it acts as a band pass filter for local spatial frequency [5]. Texture features can be extracted from highly specific frequency and orientation characteristics .The major disadvantage of Gabor filter its large computational complexity. Gabor filter banks result in redundant features at different scales due to the non-orthogonality of Gabor functions.

Wavelet transform has become a common tool in image processing and in fabric defect detection. The concept of wavelet transform was proposed by Mallat (1989)

[6].Wavelet transform is widely used for fabric defect detection [7,8,9]. Many researches depend on combination of wavelet transform and other methods such as Gaussian mixture model technique [10,11],Gabor filters [12],Independent component analysis [13],genetic algorithm [14] and back propagation neural network [15]. Few researches have been carried out to detect defects in patterned fabric using wavelet transform. Our proposed approach is concentrated on patterned fabric. First, we use Autocorrelation to extract pattern, then multiresolution analysis of the à trous wavelet with the stages of image smoothing to extract approximate sub-image at an appropriate level. Our research aims to enhance energy of defective area and give very low enhancement for back ground. Then, we threshold the sub-image using statistical energy calculations.

This paper is organized as follow, Section 2 shows literature review of different methods for fabric defect detection. Section 3 includes steps of fabric defect detection using à trous wavelet decomposition. Section 4 shows detailed evaluation of our proposed method. Conclusion is given in Section 5.

2. Literature Review

Wavelet transform has been developed for over 25 years. The multi-resolution technique can be performed with different algorithms Mallet and à trous [7]. Mallet algorithm is based on representing the wavelet transform as a pyramid as shown in Figure 1.This figure shows that the base of the pyramid is the original image A_2^j with C columns and R rows. In each level of the pyramid the numbers of columns and rows are reduced because of the sub sampling.

In 1990, à torus algorithm was proposed by Holschneid and tchamitchian [17]. In this case the image decomposition scheme can be represented with a parallelepiped as shown in Figure 2. The base of the parallelepiped is the original image A_2^j with C columns and R rows. This figure shows the approximation detail at N levels with the same number of rows and columns as, in the original image.

The original image first passes through two low pass filters to generate the approximate details then the horizontal ,

vertical, and diagonal details are generated from the difference between the original image and the approximate image. The energy of the image is focused in low frequency sub-band image of Fabric textile.

2.1 Defect Detection By Selecting A Suitable Subset Of Wavelet Coefficients Through Genetic Algorithm.

This method depends on genetic algorithm and it has two phases. The first one is extracting all wavelet coefficients from a perfect fabric image by using two separable filters for horizontal and vertical direction to get the filtered image F [14].

$$F = W_1 * U * W_2^T \quad (1)$$

where W_1 is the wavelet coefficient in the horizontal direction, W_2 is the wavelet coefficient in the vertical direction and U is the perfect image. Then, the second one gives a suitable subset of all coefficients using genetic algorithm by calculating fitness function for filtered image using equation (2), (3).

$$sum = \sum_{i=1}^n \sum_{j=1}^m F(i,j)^2 \quad (2)$$

$$H = - \sum_{i=1}^n d(i) * \log_2(d(i)) \quad (3)$$

$$J = \sum_{i=1}^n \sum_{j=1}^m (W_1 * U * W_2^T)^2 \quad (4)$$

$$J = Entropy(W_1 * U * W_2^T) \quad (5)$$

where H is the entropy function and J is the normal form of high frequency components of image. The subset can delete the main fabric of the image and detect defects of fabric textile. This method is applied on unpatterned fabric.

2.2 Direct Thresholding Using Wavelet Transform Detailed Subimage

This is a method of direct thresholding (DT) that was proposed by Ngan(2005)[18]. Firstly, histogram equalization is applied on the image. Then wavelet transform is performed with level four to get vertical and horizontal details. Lower and upper bound are obtained among all pixel values in the detailed horizontal and vertical sub-images to determine threshold values as shown in Figure (3).

The threshold values should be $[0.97*t_{lower}, 0.97*t_{upper}]$ to reduce noise. The average value of minimum and maximum values of the horizontal detail of level four is calculated and the same process is repeated for vertical details at level four. These threshold values are used to threshold the tested image at level four. Finally, OR operation of horizontal and vertical details is performed and smoothing filter is applied to remove noise. The main disadvantage of this method is that most of the image energy of is concerned on the low

frequency sub-band. So, fusion of the horizontal and vertical sub-images doesn't produce satisfactory results. The overall detection success is 88.3%

2.3 Stitching Defect Detection Using Back Propagation Algorithm

This method was suggested by WONG, Keung[15]. The proposed stages are illustrated in Figure (4). This method has two phases. The first one is stitching defect segmentation module. In this module, wavelet transform is applied first on the input image at an appropriate level then the sub bands are filtered using quadrant mean filter. A threshold is applied on the image to segment the defective area from texture background then apply noise filtering to obtain the binary image.

The second phase is the classification module. In this module the image features that contain defective regions are extracted. It uses the Back Propagation neural network to classify the pattern. Multilayer feed forward network with differential transfer function is used.

3. Proposed Approach Based on Additive Wavelet Transform

The proposed method is illustrated in Figure (5). It consists of calculating texture primitive size using auto correlation. Then, apply à trous wavelet transform on the input image at an appropriate level using statistical calculation to define the thresholding values. All input images are of size 256*256 pixel with 8-bit gray level.

3.1 Autocorrelation

Pattern fabric is defined as fabric with regular texture primitive. Autocorrelation function is used to extract repeated pattern unit and calculate its size [19,20]. We calculate autocorrelation in horizontal and vertical direction of image. Equations (9) and (10) illustrate autocorrelation functions in horizontal and vertical directions respectively.

$$C_{x,0} = \frac{\frac{1}{M*(N-x)} \sum_{i=1}^{N-x} \sum_{j=i}^M G_{i,j} * G_{i+x,y}}{\frac{1}{M*N} \sum_{i=1}^N \sum_{j=1}^M G_{i,j}^2} \quad (9)$$

$$C_{0,y} = \frac{\frac{1}{N*(M-y)} \sum_{i=1}^N \sum_{j=i}^{M-y} G_{i,j} * G_{i,j+y}}{\frac{1}{M*N} \sum_{i=1}^N \sum_{j=1}^M G_{i,j}^2} \quad (10)$$

where $M \times N$ size of original image. $G_{i,j}$ is the gray pixel value at (i, j) . $C_{x,0}$ and $C_{0,y}$ are autocorrelation values of x and y respectively. The periodicity in the vertical and horizontal directions give the size of repeated pattern.

3.2 The "à trous" wavelet transform algorithm

It is a discrete approach of wavelet transform [16, 20]. The advantage of this algorithm is the shift invariance. This method was used in many applications such as signal analysis, data fusion and pattern recognition [21,22, 23]. Our proposed approach uses à trous wavelet transform to decompose the image into wavelet planes. Given an image p , we form the sequence of approximation as follows :-

$$F_1(P) = P_1, F_2(P_1) = P_2, F_3(P_2) = P_3, \dots$$

where $F_1(P)$ is the approximate image at level 1. To form this sequence, the algorithm performs successive convolutions with a filter obtained from an auxiliary function called scaling function. The 2-D low-pass filter is generated from cubic B-spline by using scaling function. Equation (11) illustrates the convolution mask M .

$$M = \begin{pmatrix} 1 & 4 & 6 & 4 & 1 \\ 4 & 16 & 24 & 16 & 4 \\ 6 & 24 & 36 & 24 & 6 \\ 4 & 16 & 24 & 16 & 4 \\ 1 & 4 & 6 & 4 & 1 \end{pmatrix} \quad (11)$$

The wavelet planes are calculated from the difference between two consecutive approximations.

$$\text{Let } W_L = P_{L-1} - P_L \quad (L=1, 2, 3, \dots, n)$$

where $P_0 = P$, P_L are versions of original image at increasing scale (decreasing resolution) and W_L are multi-resolution wavelet planes.

3.3 Defect Detection Procedures On Patterned Fabric Using à trous Wavelet Transform.

In patterned fabric, when the approximate sub-image of à trous wavelet transform (WT) is extracted, the change in energy of defective and non defective image is observed as shown in Figure (6). Three examples of longitudinal diagram of energy on row and column of non defective and defective fabric images are shown in Figure (6), respectively. There are obvious changes in energy in longitudinal diagram. The change appears in row energy(e) but the change appears in column energy(i). The maximum energy in row energy of un defected image (a) = $6.0917e+05$ and the maximum energy in row energy of defected image (d) = $1.0367e+06$ as shown in table (1). The maximum energy in column energy of un defected image (a) = $6.2900e+05$ and the maximum energy in column energy of defected image (d) = $9.9701e+05$ as shown in table (1). It is observed that maximum energy in row energy in defected image(d) greater than maximum energy in row energy of un defected image(a). Also, it is observed that maximum energy in column energy in defected image (g) greater than maximum energy in column energy of un defected image (a).

The proposed approach is divided into two steps:-

A. Training Steps

1. We use four reference images.
2. We extract the size of repetitive pattern using autocorrelation.
3. We apply à trous WT to extract the corresponding approximate sub-image of appropriate level.
4. We divide the image to blocks of size $p \times q$.
5. We calculate energy for each row in each block.

$$E_r = \sum_{i=1}^q |x(i)|^2 \quad (12)$$

The row energy in each block is namely as $\{E_{r1}, E_{r2}, E_{r3}, \dots, E_{rn}\}$. Maximum energy and minimum energy are obtained for rows in each block namely as $\{E_{max}^1, E_{max}^2, \dots, E_{max}^n\}$, where n is the number of blocks in image.

6. We repeat the same procedures for the columns of the approximate sub-image.
7. We obtain the maximum and the minimum values of the four approximate sub-images to get threshold values $\{T_{min}^{row}, T_{max}^{row}, T_{min}^{col}, T_{max}^{col}\}$

B. Testing Steps

The steps of the testing phase are:

1. We apply à trous WT to extract the approximate sub-image of appropriate level.
2. We divide image to blocks of size $p \times q$.
3. We calculate energy for each row and column in each block using Equation. (12).
4. We threshold each row and column in each block by thresholding values from training step and obtain F_{row}, F_{column} .
5. We combine the thresholded results for rows and columns energy. Determine whether the test image is defected or not.

4. Detailed Evaluation Based on Dot-Patterned and Box-Patterned and Star-Patterned

4.1. Simulation Results

*Data Set Description.

The performance of the proposed algorithm is evaluated using 145 samples (Box patterned, Dot patterned and star patterned) [25] as shown in table (2). The defected images have different kinds of defects (broken end, knots, hole, thick bar and thin bar). All input images have size of 256×256 pixels in gray level scale.

Table2. Description of data set

Shape of image pattern	No. of un defected images	No. of defective images
Box pattern	30	20
Dot pattern	25	25
Star pattern	25	20

*Performance Evaluation

The performance of the proposed algorithm is determined by accuracy [24].

*Metric parameter

Accuracy is evaluated in terms of true positive (TP), true negative (TN), false positive (FP), and false negative (FN) as shown in Table 2. The TP is the number of defected images identified as defected. The TN is the number of defect free identified as defect free. The FP is the number of defect free identified as defective. The FN is the number of

defective images identified as defect free. The formula of accuracy is defined in equation (13).

$$\text{Accuracy (A)} = (\text{TP} + \text{TN}) / (\text{TP} + \text{FP} + \text{TN} + \text{FN}) \quad (13)$$

The accuracy of the proposed algorithm in comparison to the algorithm in [18] is shown in Table (3).

***Results Analysis and discussion**

The Detection success is shown in table 3. This table show how many images get correct detection and how many images get false detection. The accuracy of the proposed approach is better than the accuracy of DT method [18] as illustrated in Table4. The accuracy increased by approximately 6% when applied on Dot pattern shape. Also it increased by 4% when applied on Box pattern shape. The proposed approach applied on star pattern shape gives accuracy equal 91.1% while DT method not applied.

Table3. Summary of the obtained results.

Pattern shape	TN	TP	FP	FN
Dot patterned	25	22	0	3
Box patterned	30	16	0	4
Star patterned	25	16	0	4

Table 4. Comparison between accuracy of DT and proposed algorithm.

Fabric type	DT[18] wavelet	proposed Additive
Dot Pattern	88.3%	94%
Box patterned	88.3%	92%
Star patterned	Not applied	91.1%

4.2.Effect due to the shape of pattern.

The dot patterned images give the best results with à trous wavelet at level 1 as shown in Figure (7). The Box patterned images give the best results at level 1 as shown in Figure (8). The Star patterned images give the best results at the test image at level 4 as shown in Figure (9). The shape of the pattern control the level of à trous wavelet.

5. Conclusion

In this paper, a method of additive à trous wavelet transform was presented for fabric defect detection based on statistical thresholding. The advantage of this method is that it gives more accurate results on patterned fabric using wavelet transform. The concept of using à trous wavelet transform to enhance energy of defective region compared to non defective region. This concept is based on the idea that the approximate sub-image contains the most of the energy at low frequency.

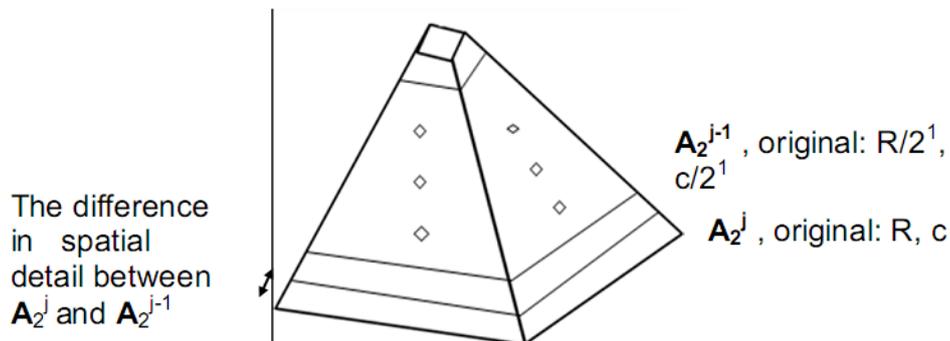


Figure1. Pyramidal representation algorithm of Mallat

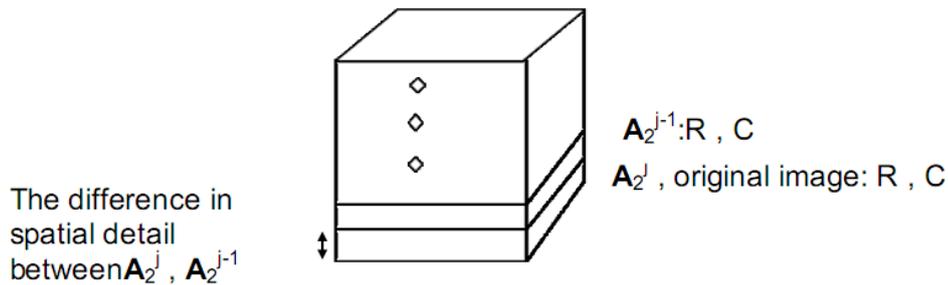


Figure 2 Parallelepiped representation algorithm of à trous

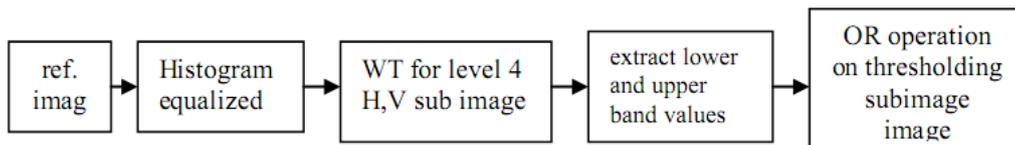


Figure 3 Direct thresholding using wavelet transform

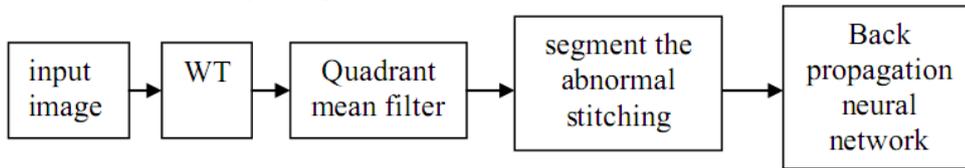


Figure 4 Stages of stitching defect detection using BP

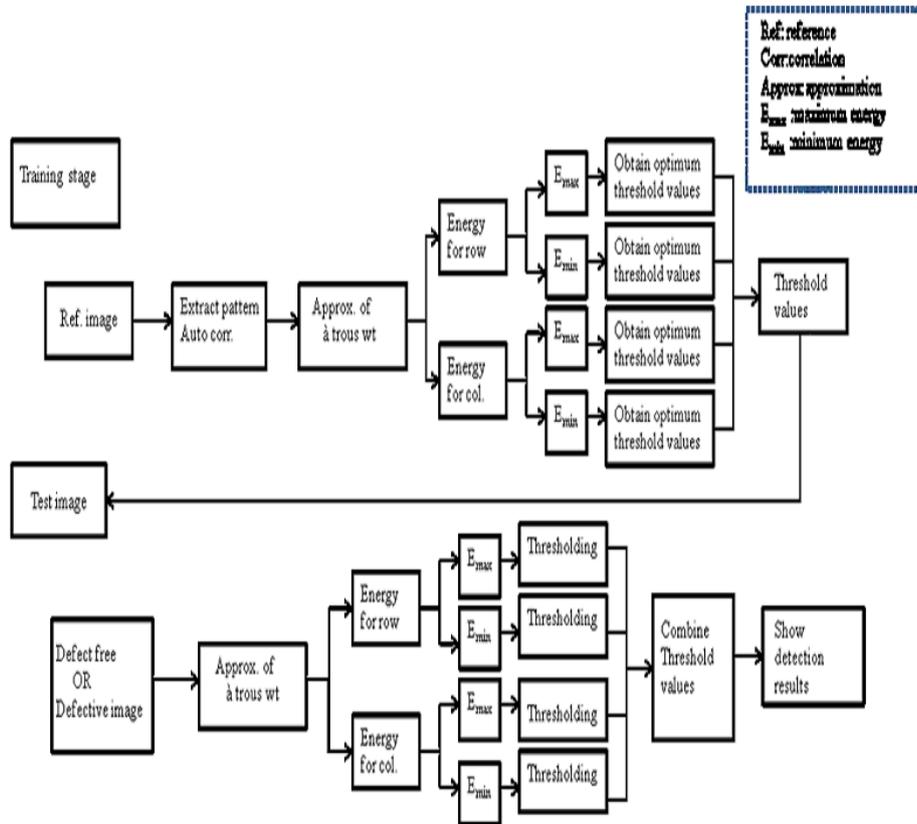


Figure 5. proposed approach Block diagram.

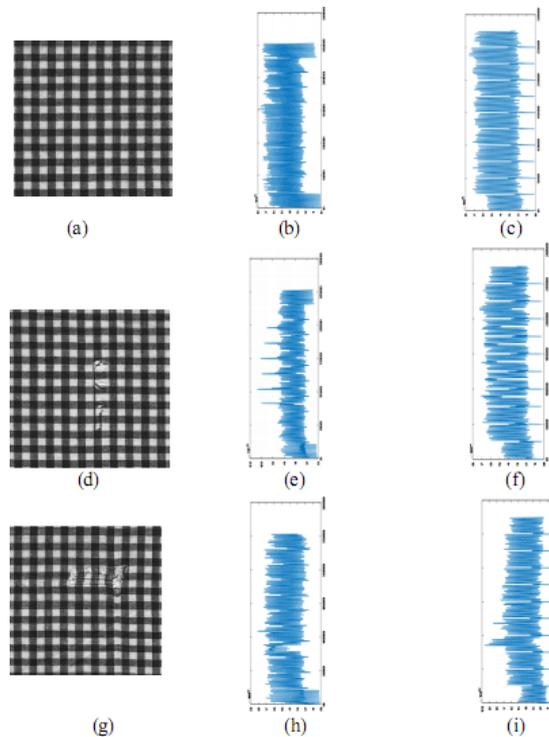


Figure 6 (a)Histogram equalized reference image. (b) Longitudinal diagram of row energy. (c) Longitudinal diagram of column energy .(d)Defected image.(e) Longitudinal diagram of row energy (change appear in row). (f) Longitudinal diagram of column energy.(g)Defected image.(h) Longitudinal diagram of row energy.(i) Longitudinal diagram of column energy (change appear in column).

Table1. Comparison between the maximum and the minimum values of rows and column for defect free image and defected image.

image	maximum value of rows	minimum value of rows	maximum value of columns	minimum value of columns
Defect free image (a)	6.0917e+05	7.6061e+04	6.2900e+05	7.6552e+04
Defected image (d)	1.0367e+06	8.2985e+04	7.3269e+05	7.4187e+04
Defected image (g)	6.8925e+05	7.5436e+04	9.9701e+05	7.7821e+04

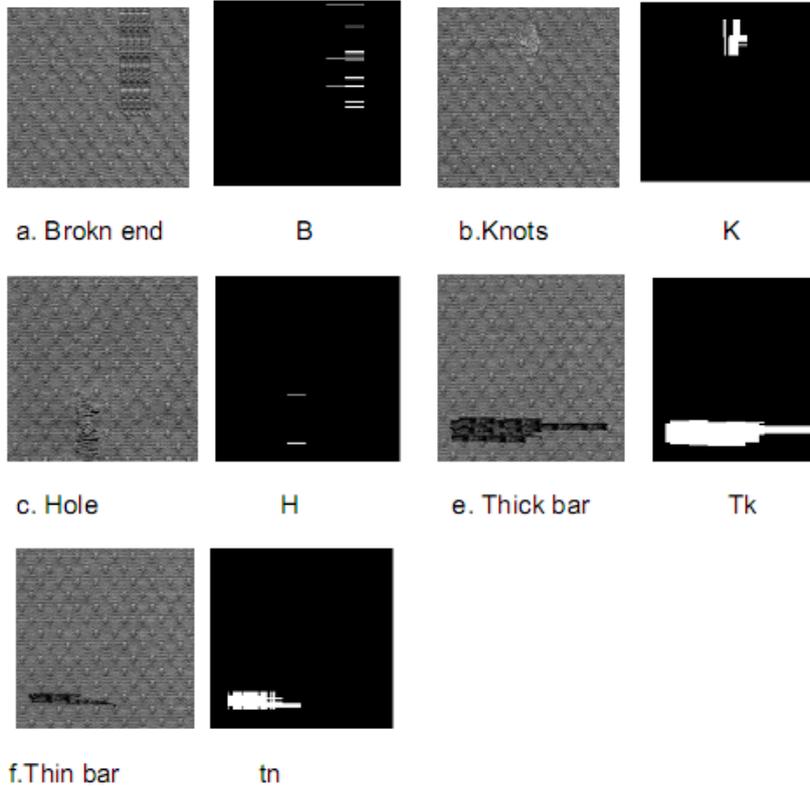


Figure 7. Results of defective Dot patterned images(broken end , Knots, holes, netting multiple, dirty yarn (thick bar and thin bar) in level(1).

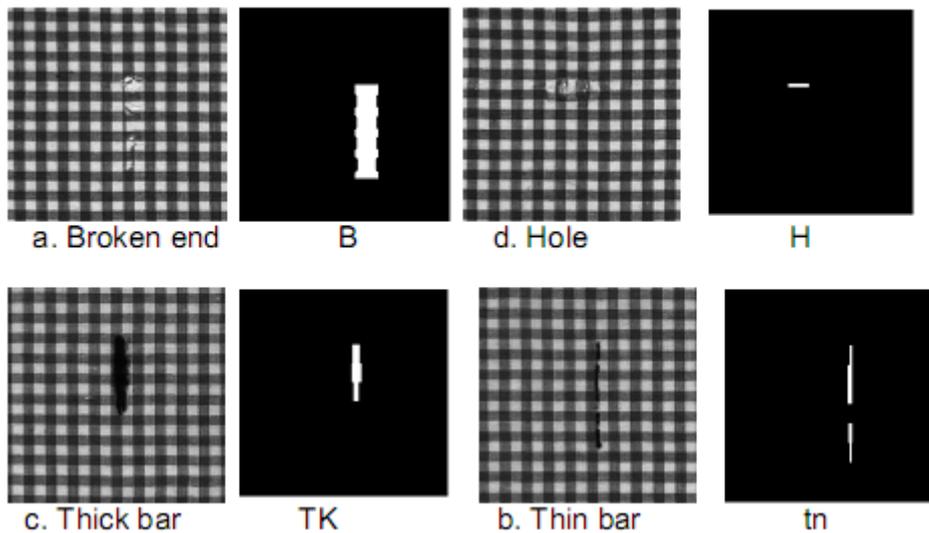


Figure 8. Results of defected Box patterned images(broken end , thin bar , thick bar , hole) at level 1.

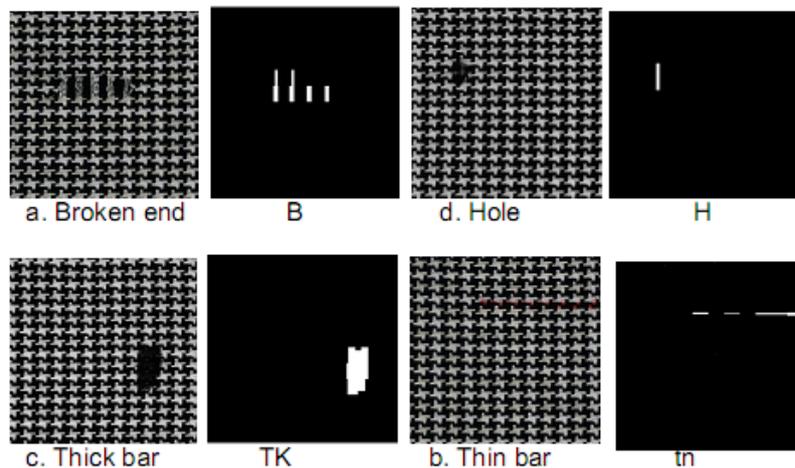


Figure 9. Results of defected Box patterned images(broken end , thin bar , thick bar , hole) at level 4.

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