CHAPTER – 4

SOME APPROACHES FOR DEFECT DETECTION THROUGH PERIODICITY EXTRACTION

4.1 Introduction

Periodically patterned textures are often found in day-to-day applications such as ceramic tiles, wallpapers, fabrics and decorations and are of great significance because of the appealing visual effects that they produce. However, the problem with repeating patterns is to locate a defective pattern if contained within such textures. Detection of defects in images with such periodically repeating patterns is visually and also computationally more complex because of the high similarity between the repeating patterns. Thus, both periodicity extraction and defect detection in periodically patterned textures are challenging problems. As a result, most of the methods in the literature assume that the size of the periodic blocks in the test image is known. In our present approach, we try to find the defective periodic blocks from the defective test image in an unsupervised way. If a method is to be devised for finding the defects in an unsupervised way, the size of the basic block of the texture in the repeating background should be computed by extracting the periodicity of the repeating structure. In our present approach, we automate the periodicity extraction from the textures and try to find the defective periodic blocks without any training stage. Among all other applications, since fabric images are prone to have several types of defects, several fabric images with defects such as broken end, hole, thin bar, thick bar, netting multiple, and knot are considered for evaluating the defect detection methods. However, our methods can be used in any application involving periodically repeating patterns.

This chapter consists of a brief description of the database of fabric images containing defects along with results of periodicity extraction from these defective images, our defect detection approaches, test results, performance evaluation, analysis on computational time and summary of all our defect detection methods.
4.2 Database of test images

The database includes defective fabric images belonging to three major wallpaper groups, namely, pmm, p2 and p4m as shown in Figs. 4.1 through 4.16. The defects in these figures, viz., broken end, hole, thin bar, thick bar, netting multiple, and knot are abbreviated as b, h, t, tt, n, and k, respectively. Because our method of automatic extraction of periodicity works on the concept of superposition, the summing-up action on DMFs is like averaging. Hence, the method yields average periodicities along row and column directions and thereby the average size of periodic blocks by averaging the effects of variations in size, shape and intensity among all periodic blocks. The same statement is valid for fabric images with defects when the concept of superposition is applied over defective and defect-free periodic blocks also. Plots of second forward difference on summed up row DMFs and summed up column DMFs are shown in Figs. 4.17 through 4.46, Figs. 4.47 through 4.71, and Figs. 4.72 through 4.97 for the defective pmm, p2 and p4m images, respectively. Since the test images with defects in the database are real fabrics with noises and distortions, the maxima captured from the plot of second forward difference on summed up DMFs from a single defective image may not yield correct periodicity. Hence, in order to arrive at appropriate row and column periodicities for each wallpaper group, frequency plots (Figs. 4.98-4.100) are made from the maxima extracted from the second derivative plots. Row or column periodicity with high frequency of occurrence is considered for arriving at the average size of the test images for each wallpaper group. This approach of selecting the periodicity with high frequency of occurrence eliminates the low frequency data resembling noises. Row periodicities for pmm, p2 and p4m images are found to be 27 pixels, 21 pixels and 26 pixels, respectively. Column periodicities for pmm, p2 and p4m images are found to be 36 pixels, 16 pixels and 24 pixels, respectively. Accordingly, periodic block sizes for pmm, p2 and p4m defective images are 36 × 27, 16 × 21, and 24 × 26, respectively as seen in Figs. 4.98, 4.99 and 4.100. Based on the sizes of periodic blocks, the total number of periodic blocks (when counted from all four corners) for each test image is given in Table-4.1 for all wallpaper groups.

* Database of defective fabric images was provided by Dr. Henry Y. T. Ngan, Research Associate of Industrial Automation Research Laboratory, Department of Electrical and Electronic Engineering, The University of Hong Kong.
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Fig. 4.2: Pmm fabric images with defect – hole.
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Fig. 4.4: Pmm fabric images with defect – *thick bar*. 
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Fig. 4.22: (a) Second forward difference of summed up row-DMF and (b) Second forward difference of summed up column-DMF for pmm image with hole defect#1.
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Fig. 4.31: (a) Second forward difference of summed up row-DMF and (b) Second forward difference of summed up column-DMF for pmm image with thin bar defect#5.

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Fig. 4.34: (a) Second forward difference of summed up row-DMF and (b) Second forward difference of summed up column-DMF for pmm image with thick bar defect#3.
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Fig. 4.42 : (a) Second forward difference of summed up row-DMF and (b) Second forward difference of summed up column-DMF for pmm image with knot defect#1.
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Fig. 4.44 : (a) Second forward difference of summed up row-DMF and (b) Second forward difference of summed up column-DMF for pmm image with knot defect#3.
Fig. 4.45: (a) Second forward difference of summed up row-DMF and (b) Second forward difference of summed up column-DMF for pmm image with knot defect #4.

Fig. 4.46: (a) Second forward difference of summed up row-DMF and (b) Second forward difference of summed up column-DMF for pmm image with knot defect #5.
Fig. 4.47: (a) Second forward difference of summed up row-DMF and (b) Second forward difference of summed up column-DMF for p2 image with broken end defect#1.

Fig. 4.48: (a) Second forward difference of summed up row-DMF and (b) Second forward difference of summed up column-DMF for p2 image with broken end defect#2.
Fig. 4.49 : (a) Second forward difference of summed up row-DMF and (b) Second forward difference of summed up column-DMF for p2 image with broken end defect#3.

Fig. 4.50 : (a) Second forward difference of summed up row-DMF and (b) Second forward difference of summed up column-DMF for p2 image with broken end defect#4.
Fig. 4.51: (a) Second forward difference of summed up row-DMF and (b) Second forward difference of summed up column-DMF for p2 image with broken end defect#5.

Fig. 4.52: (a) Second forward difference of summed up row-DMF and (b) Second forward difference of summed up column-DMF for p2 image with hole defect#1.
Fig. 4.53: (a) Second forward difference of summed up row-DMF and (b) Second forward difference of summed up column-DMF for p2 image with hole defect#2.

Fig. 4.54: (a) Second forward difference of summed up row-DMF and (b) Second forward difference of summed up column-DMF for p2 image with hole defect#3.
Fig. 4.55: (a) Second forward difference of summed up row-DMF and (b) Second forward difference of summed up column-DMF for p2 image with hole defect#4.

Fig. 4.56: (a) Second forward difference of summed up row-DMF and (b) Second forward difference of summed up column-DMF for p2 image with hole defect#5.
Fig. 4.57: (a) Second forward difference of summed up row-DMF and (b) Second forward difference of summed up column-DMF for p2 image with thin bar defect#1.

Fig. 4.58: (a) Second forward difference of summed up row-DMF and (b) Second forward difference of summed up column-DMF for p2 image with thin bar defect#2.
Fig. 4.59 : (a) Second forward difference of summed up row-DMF and (b) Second forward difference of summed up column-DMF for p2 image with thin bar defect#3.

Fig. 4.60 : (a) Second forward difference of summed up row-DMF and (b) Second forward difference of summed up column-DMF for p2 image with thin bar defect#4.
Fig. 4.61: (a) Second forward difference of summed up row-DMF and (b) Second forward difference of summed up column-DMF for p2 image with thin bar defect#5.

Fig. 4.62: (a) Second forward difference of summed up row-DMF and (b) Second forward difference of summed up column-DMF for p2 image with thick bar defect#1.
Fig. 4.63: (a) Second forward difference of summed up row-DMF and (b) Second forward difference of summed up column-DMF for p2 image with thick bar defect#2.

Fig. 4.64: (a) Second forward difference of summed up row-DMF and (b) Second forward difference of summed up column-DMF for p2 image with thick bar defect#3.
Fig. 4.65:  (a) Second forward difference of summed up row-DMF and (b) Second forward difference of summed up column-DMF for p2 image with thick bar defect#4.

Fig. 4.66:  (a) Second forward difference of summed up row-DMF and (b) Second forward difference of summed up column-DMF for p2 image with thick bar defect#5.
Fig. 4.67: (a) Second forward difference of summed up row-DMF and (b) Second forward difference of summed up column-DMF for p2 image with netting multiple defect#1.

Fig. 4.68: (a) Second forward difference of summed up row-DMF and (b) Second forward difference of summed up column-DMF for p2 image with netting multiple defect#2.
Fig. 4.69 : (a) Second forward difference of summed up row-DMF and (b) Second forward difference of summed up column-DMF for p2 image with netting multiple defect#3.

Fig. 4.70 : (a) Second forward difference of summed up row-DMF and (b) Second forward difference of summed up column-DMF for p2 image with netting multiple defect#4.
Fig. 4.71: (a) Second forward difference of summed up row-DMF and (b) Second forward difference of summed up column-DMF for p2 image with netting multiple defect#5.

Fig. 4.72: (a) Second forward difference of summed up row-DMF and (b) Second forward difference of summed up column-DMF for p4m image with broken end defect#1.
Fig. 4.73:  (a) Second forward difference of summed up row-DMF and (b) Second forward difference of summed up column-DMF for p4m image with broken end defect#2.

Fig. 4.74:  (a) Second forward difference of summed up row-DMF and (b) Second forward difference of summed up column-DMF for p4m image with broken end defect#3.
Fig. 4.75: (a) Second forward difference of summed up row-DMF and (b) Second forward difference of summed up column-DMF for p4m image with broken end defect#4.

Fig. 4.76: (a) Second forward difference of summed up row-DMF and (b) Second forward difference of summed up column-DMF for p4m image with broken end defect#5.
Fig. 4.77: (a) Second forward difference of summed up row-DMF and (b) Second forward difference of summed up column-DMF for p4m image with hole defect#1.

Fig. 4.78: (a) Second forward difference of summed up row-DMF and (b) Second forward difference of summed up column-DMF for p4m image with hole defect#2.
Fig. 4.79: (a) Second forward difference of summed up row-DMF and (b) Second forward difference of summed up column-DMF for p4m image with hole defect#3.

Fig. 4.80: (a) Second forward difference of summed up row-DMF and (b) Second forward difference of summed up column-DMF for p4m image with hole defect#4.
Fig. 4.81: (a) Second forward difference of summed up row-DMF and (b) Second forward difference of summed up column-DMF for p4m image with hole defect#5.

Fig. 4.82: (a) Second forward difference of summed up row-DMF and (b) Second forward difference of summed up column-DMF for p4m image with thin bar defect#1.
Fig. 4.83: (a) Second forward difference of summed up row-DMF and (b) Second forward difference of summed up column-DMF for p4m image with thin bar defect#2.

Fig. 4.84: (a) Second forward difference of summed up row-DMF and (b) Second forward difference of summed up column-DMF for p4m image with thin bar defect#3.
Fig. 4.85: (a) Second forward difference of summed up row-DMF and (b) Second forward difference of summed up column-DMF for p4m image with thin bar defect#4.

Fig. 4.86: (a) Second forward difference of summed up row-DMF and (b) Second forward difference of summed up column-DMF for p4m image with thin bar defect#5.
Fig. 4.87: (a) Second forward difference of summed up row-DMF and (b) Second forward difference of summed up column-DMF for p4m image with thick bar defect#1.

Fig. 4.88: (a) Second forward difference of summed up row-DMF and (b) Second forward difference of summed up column-DMF for p4m image with thick bar defect#2.
Fig. 4.89: (a) Second forward difference of summed up row-DMF and (b) Second forward difference of summed up column-DMF for p4m image with thick bar defect#3.

Fig. 4.90: (a) Second forward difference of summed up row-DMF and (b) Second forward difference of summed up column-DMF for p4m image with thick bar defect#4.
Fig. 4.91: (a) Second forward difference of summed up row-DMF and (b) Second forward difference of summed up column-DMF for p4m image with thick bar defect#5.

Fig. 4.92: (a) Second forward difference of summed up row-DMF and (b) Second forward difference of summed up column-DMF for p4m image with thick bar defect#6.
Fig. 4.93: (a) Second forward difference of summed up row-DMF and (b) Second forward difference of summed up column-DMF for p4m image with netting multiple defect#1.

Fig. 4.94: (a) Second forward difference of summed up row-DMF and (b) Second forward difference of summed up column-DMF for p4m image with netting multiple defect#2.
Fig. 4.95: (a) Second forward difference of summed up row-DMF and (b) Second forward difference of summed up column-DMF for p4m image with netting multiple defect#3.

Fig. 4.96: (a) Second forward difference of summed up row-DMF and (b) Second forward difference of summed up column-DMF for p4m image with netting multiple defect#4.
Fig. 4.97: (a) Second forward difference of summed up row-DMF and (b) Second forward difference of summed up column-DMF for p4m image with netting multiple defect#5.

Fig. 4.98: Frequency plots for pmm defective images for (a) row periodicity and (b) column periodicity.
Fig. 4.99 : Frequency plots for p2 defective images for (a) row periodicity and (b) column periodicity.

Fig. 4.100 : Frequency plots for p4m defective images for (a) row periodicity and (b) column periodicity.
Table – 4.1: Details on database of the defective test images

<table>
<thead>
<tr>
<th>Wallpaper group</th>
<th>Defect</th>
<th>No. of test images</th>
<th>Total no. of periodic blocks</th>
</tr>
</thead>
<tbody>
<tr>
<td>pmm</td>
<td>Broken end</td>
<td>5</td>
<td>1260</td>
</tr>
<tr>
<td>pmm</td>
<td>Hole</td>
<td>5</td>
<td>1260</td>
</tr>
<tr>
<td>pmm</td>
<td>Thin bar</td>
<td>5</td>
<td>1260</td>
</tr>
<tr>
<td>pmm</td>
<td>Thick bar</td>
<td>5</td>
<td>1260</td>
</tr>
<tr>
<td>pmm</td>
<td>Netting multiple</td>
<td>5</td>
<td>1260</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>30</td>
<td>7560</td>
</tr>
<tr>
<td>p2</td>
<td>Broken end</td>
<td>5</td>
<td>1920</td>
</tr>
<tr>
<td>p2</td>
<td>Hole</td>
<td>5</td>
<td>1920</td>
</tr>
<tr>
<td>p2</td>
<td>Thin bar</td>
<td>5</td>
<td>1920</td>
</tr>
<tr>
<td>p2</td>
<td>Thick bar</td>
<td>5</td>
<td>1920</td>
</tr>
<tr>
<td>p2</td>
<td>Netting multiple</td>
<td>5</td>
<td>1920</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>25</td>
<td>9600</td>
</tr>
<tr>
<td>p4m</td>
<td>Broken end</td>
<td>5</td>
<td>1800</td>
</tr>
<tr>
<td>p4m</td>
<td>Hole</td>
<td>5</td>
<td>1800</td>
</tr>
<tr>
<td>p4m</td>
<td>Thin bar</td>
<td>5</td>
<td>1800</td>
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<tr>
<td>p4m</td>
<td>Thick bar</td>
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<tr>
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<td>Netting multiple</td>
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<td>1800</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>26</td>
<td>9360</td>
</tr>
</tbody>
</table>

4.3 Defect detection methods based on Human Vision Perception (HVP)

Texture is a key component of human vision perception. When defects are present in texture, human vision can easily identify the defects. Hence, features that correspond to human vision perception can be considered to be good measures for defect detection. With respect to human perception of textures, considerable work has been performed in the psychological fields. Julesz verified that the discrimination of textures depends mostly on the difference in second-order statistics (Julesz, 1962). However, the work is directed towards the extreme behavior of the perceptual mechanism for studying the extent to which one can just perceive differences in artificially produced patterns when all familiar cues are removed. Moreover, features
that depend on second-order statistics such as features of gray level co-occurrence matrices proposed by Haralick et al. (1973) involve huge computational time. In Computational Theory and Image Analysis literature, human texture vision has been studied from two views. The first focuses on the neuro-physiological aspects of human visual perception (eg. Daugman, 1980 and 1987; Turner, 1986; Manjunath and Ma, 1996; Manjunath et al. 2000). The second view examines the psychophysical (perceptual) aspects as explored by Tamura et al. (1978). According to Daugman (1987), the human visual system is concerned with extracting information jointly in the 2D space domain and in the 2D frequency domain. Because of the incompatibility of these two demands, research work has evolved towards the optimal solution via 2D channels that roughly approximate 2D Gabor filters. Textural features corresponding to human visual perception as suggested by Tamura et al. (1978) are very useful for optimum feature selection and texture analyzer design. In comparison with psychological measurements for human subjects, the computational measures suggested by them gave good correspondences in rank correlation for 16 typical texture patterns from Brodatz album. Hence, this section focuses on defect defection based on the concept of human vision perception using 2D Gabor wavelets and Tamura features.

4.3.1 Gabor wavelet based method*

4.3.1.1 Introduction

In visual perception of real-world, Gabor wavelets capture the properties of spatial localization, orientation selectivity, spatial frequency selectivity, and quadrature phase relationship and are good approximation to the filter response profiles encountered experimentally in cortical neurons (Lee, 1996). According to Lee (1996), the coding of Gabor filter is based on the imitation of human vision system. Moreover, simple cells of visual cortex of humans having receptive fields are restricted to small regions of space and are highly structured. They are having three important characteristics, viz., band pass, orientation selectivity, and direction

* The proposed method of defect detection based on Gabor wavelets has been presented in the 5th International Conference on Information Processing (ICIP-2011) held at Bangalore, India, during 5-7 August 2011, under the title “Automatic detection of texture defects using texture-periodicity and Gabor wavelets.”

selectivity. They respond differently to the stimuli with different spatial frequencies, orientation, and directions. The Gabor wavelets are self-similar as these can be generated from one wavelet through scaling and rotation via the wave vector. Each Gabor wavelet is a product of a Gaussian envelope and a complex wave with real and imaginary parts. Gabor wavelets are widely used for image analysis because of their biological relevance and computational properties and are defined as follows (Lee, 1996):

$$\psi_{\theta, \nu}(z) = \frac{k_{\theta, \nu}^2}{\sigma^2} \exp\left( -\frac{k_{\theta, \nu}^2 z^2}{2\sigma^2} \right) \exp\left( ik_{\theta, \nu} \cdot \exp\left( -\frac{\sigma^2}{2} \right) \right). \quad (4.1)$$

where $\sigma = 2\pi$. The symbols $\theta$ and $\nu$ represent the orientation and the scale of the Gabor wavelet, respectively in the spatial domain $z = (x, y)$ and the wave vector $k_{\theta, \nu}$ is given by

$$k_{\theta, \nu} = k_{\nu} \exp \left( i\theta \right). \quad (4.2)$$

where $k_{\nu} = k_{\max} f_{\nu}$; $k_{\max} = \pi/2$, $f = \sqrt{2}$. Fig. 4.101 shows typical Gabor wavelets (real and imaginary parts) of size 36 \times 27 pixels generated using 5 scales $\nu \in \{0, 1, 2, 3, 4\}$ and 8 orientations $\theta \in \{0, \pi/8, \pi/4, 3\pi/8, \pi/2, 5\pi/8, 3\pi/4, 7\pi/8\}$. The Gabor wavelet transformation of an image $I(x, y)$ can be written as

$$G_{\theta, \nu}(z) = I(x, y) \ast \psi_{\theta, \nu}(z). \quad (4.3)$$

where the symbol $\ast$ denotes the convolution operation. The output of this equation consists of real and imaginary parts that exhibit all desirable characteristics of spatial locality, scale and orientation selectivity for each Gabor wavelet. The resultant magnitude can be utilized for effective feature extraction from the test images followed by defect detection.
Fig. 4.101: (a) Real Gabor wavelets; (b) Imaginary Gabor wavelets. From left to right, the orientations are $0, \pi/8, \pi/4, 3\pi/8, \pi/2, 5\pi/8, 3\pi/4$, and $7\pi/8$ radians and from top to bottom, the scales are $0, 1, 2, 3$, and $4$ for both real and imaginary wavelets.
4.3.1.2 Proposed method

Motivated by the fact that the Gabor wavelets are of great biological relevance, we present a method of defect detection on periodically patterned textures with the help of texture-periodicity and the Gabor-space of the textures. As far as unpatterned textures (plain and twill fabrics as shown in Fig. 1.2(a) and (b)) are concerned, there is some flexibility in selecting the size of the Gabor kernels (Kumar, 2001). However, in general, more reliable measurement of texture features calls for larger window sizes, whereas, extracting finer details calls for smaller windows (Jain and Farrokhnia, 1990). For a periodic patterned texture, size of the filter can be chosen to be same as the size of the periodic block. It should be noted that images of p1 wallpaper groups do not have any symmetry within the lattices. Hence, some authors classify the unpatterned texture images (plain and twill fabrics) as images belonging to p1 wallpaper group (Ngan et al., 2010). For images belonging to wallpaper groups other than p1, there are sub-patterns within a periodic pattern. Hence, for all test images, size of the kernel is selected to be half the size of the periodic block and each input defective image is subjected to Gabor wavelet transformation using Gabor kernels in 5 scales $\nu \in \{0, 1, 2, 3, 4\}$ and 8 orientations $\theta \in \{0, \pi/8, \pi/4, 3\pi/8, \pi/2, 5\pi/8, 3\pi/4, 7\pi/8\}$ to get a resultant image in L2 norm. An image under inspection does not need to have complete number of periodic blocks always. Hence, from the resultant Gabor filtered image of size $M \times N$, four cropped images of size $M_{crop} \times N_{crop}$, each containing complete number of periodic blocks, are obtained by cropping the resultant image from all 4 corners (top-left, bottom-left, top-right and bottom-right). Size of each cropped image ($M_{crop} \times N_{crop}$) is calculated using floor operation in mathematics as

$$M_{crop} = \left\lfloor \frac{M}{p_c} \right\rfloor \times p_c \quad \text{(4.4)}$$

$$N_{crop} = \left\lfloor \frac{N}{p_r} \right\rfloor \times p_r \quad \text{(4.5)}$$

where $p_c$ is the periodicity along column direction (i.e., column-periodicity which is defined as the number of rows in a periodic block) and $p_r$ is the periodicity along row direction (i.e., row-periodicity which is defined as the number of columns in a periodic block). Because Gabor wavelets have direct relevance to human vision system, defect identification through human vision system is equivalent to defect identification based on features extracted from the Gabor-space of the image. Thus,
defective zones are enhanced in Gabor-space domain of the image and energy in L1 norm itself can be used as feature space for defect detection using cluster analysis. Each cropped image is split into several periodic blocks. Based on energy of each block in L1 norm as feature-space, Ward’s hierarchical algorithm which is based on inner squared distance and minimum variance criterion (Gonzalez and Woods, 2008) is utilized to get a cluster tree or dendrogram. This dendrogram is in the form of a linkage matrix $Z$ of size $(n_p-1) \times 3$, where $n_p$ is the number of periodic blocks. The leaf nodes in the cluster hierarchy are the periodic blocks in the original data set numbered from 1 to $n_p$. These are the singleton clusters from which all higher clusters are built (Matlab toolbox). Each newly formed cluster, corresponding to row $i$ in $Z$, is assigned the index $n_p+i$. The first and second columns of the linkage matrix contain the indices of the periodic blocks that were linked in pairs to form a new cluster. This new cluster is assigned the index value $n_p+i$. There are $n_p-1$ higher clusters corresponding to the interior nodes of the hierarchical cluster tree. The third column contains the corresponding linkage distances between the periodic blocks paired in the clusters at each row $i$. The last value of the linkage distance is maximum indicating that all periodic blocks are grouped into one cluster and the last but one value of the linkage distance is the next maximum corresponding to two clusters yielding the required cut-off point at which two clusters (one cluster containing defective periodic blocks and other cluster containing defect-free periodic blocks) are formed. Upon identifying the two clusters, the number of periodic blocks in one cluster is compared with that of the other and the cluster with less number of periodic blocks is assumed to be defective.

4.3.1.3 Illustration of the proposed method

In order to illustrate the proposed method of defect detection, let us consider a sample defective image (p4m image with thick bar defect - tt6) as shown in Fig. 4.15. This image is subjected to Gabor wavelet transformation in 5 scales and 8 orientations to get a resultant image in L2 norm. Fig. 4.102 shows the defective image along with the resultant image in Gabor-space.
It is very clear that the defects are highly enhanced in the Gabor-space and hence simple L1 energy in Gabor-space itself can be sufficient to discriminate defective and defect-free periodic blocks. Fig. 4.103 shows the cropped images obtained from the Gabor-space image from all four corners. Each cropped image in Gabor space is split into several periodic blocks and the L1 energy extracted from the periodic blocks is used as feature space for the hierarchical clustering.

The dissimilarity matrices obtained from the L1 energy are shown in Fig. 4.104 in gray-scale form by scaling the matrix elements linearly in the range 0–255. Dark pixels indicate closeness among the periodic blocks and bright pixels indicate high dissimilarity. The diagonal elements in the dissimilarity matrix which is symmetric clearly indicate that the periodic blocks are of zero dissimilarity with themselves. Each defective periodic block has zero dissimilarity with respect to itself, very high dissimilarity with respect to defect-free blocks, and high similarity with respect to
other defective blocks. The dendrograms obtained from the dissimilarity matrices through Ward’s hierarchical clustering are shown in Fig. 4.105 along with the defective periodic blocks identified by the clustering for all cropped images. Boundaries of the defective periodic blocks thus identified from each cropped image are highlighted using white pixels and shown in Fig. 4.106. Fig. 4.107 shows the defective blocks in image-space based on one-to-one mapping from Gabor-space to image-space.

Fig. 4.104 : Dissimilarity matrix obtained from (a) top-left (b) bottom-left (c) top-right (d) bottom-right corners of the resultant Gabor-space image shown in gray scale.
Fig. 4.105: Result of cluster analysis showing dendrograms of each dissimilarity matrix obtained from (a) top-left (b) bottom-left (c) top-right (d) bottom-right corners of the resultant Gabor-space image.

Fig. 4.106: Defective periodic blocks identified from the resultant Gabor-space image from (a) top-left (b) bottom-left (c) top-right (d) bottom-right corners.

Fig. 4.107: Defective periodic blocks shown in image space domain based on the results obtained from the resultant Gabor-space image from (a) top-left (b) bottom-left (c) top-right (d) bottom-right corners.
When there is no false positive which is defined as the number of defect-free periodic blocks identified as defective, we can get overview of defects based on defect-fusion from all defective blocks identified from each cropped image. The defect fusion for the pnm test image with thick bar defect is illustrated in Fig. A.1 in Appendix-I. This fusion involves superimposing of boundaries of defects identified from all cropped images on original image, morphological filling (Gonzalez and Woods, 2008), Canny edge detection (Gonzalez and Woods, 2008) of the morphologically filled zones and superimposing of the identified edges on the original defective image. Fig. A.1(a) shows the boundaries of the defective blocks identified from each cropped image superimposed on the Gabor space image. Fig. A.1(b) shows the boundaries of the defective blocks shown separately on plain background for clarity. Fig. A.1(c) shows the result of morphological filling. Fig. A.1(d) shows the edges of the fused zone after Canny edge detection. Fig. A.1(e) shows the identified edges shown superimposed on original defective image using white pixels.

4.3.1.4 Experimental analysis

Defective images from all three major wallpaper groups are tested and performance measures, namely, precision, recall and accuracy are evaluated for each image. These performance measures are widely used in several retrieval applications (Fawcett, 2006; Brown and Davis, 2006). These measures are evaluated based on true positive (TP), true negative (TN), false positive (FP), and false negative (FN), where true positive is defined as the number of defective periodic blocks identified as defective; true negative is defined as the number of defect-free periodic blocks identified as defect-free; false positive is defined as the number of defect-free periodic blocks identified as defective; and false negative is defined as the number of defective periodic blocks identified as defect-free. Precision is the measure of probability that the randomly selected/ retrieved objects are relevant. It is defined as the number of periodic blocks correctly labeled as belonging to the positive class divided by the total number of periodic blocks labeled as belonging to the positive class and is calculated as $TP/(TP+FP)$. Recall is the measure of probability that a relevant object is retrieved in a search. It is defined as the number of true positives divided by the sum of true positives and false negatives that are periodic blocks not labeled as belonging to the
positive class but should have been and is calculated as TP/(TP+FN). Accuracy is the measure of overall success rate that considers detection rates of both defective and defect-free periodic blocks and is calculated as (TP+TN)/(TP+TN+FP+FN). Though the number of periodic blocks taken from a defective input image is same for all of its cropped images, the number of defective periodic blocks identified does not need to be same for all cropped images. This is because the contribution of defect in each periodic block may differ for different cropped images. Hence the performance measures are averaged for all cropped images of the test images and given in Table 4.2.

### Table 4.2: Performance parameters for Gabor wavelet based method of defect detection

<table>
<thead>
<tr>
<th>Wallpaper group</th>
<th>Defect</th>
<th>Precision (%)</th>
<th>Recall (%)</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>pmm</td>
<td>Broken end</td>
<td>73.57</td>
<td>67.02</td>
<td>79.36</td>
</tr>
<tr>
<td>pmm</td>
<td>Hole</td>
<td>52.41</td>
<td>85.76</td>
<td>83.33</td>
</tr>
<tr>
<td>pmm</td>
<td>Thin bar</td>
<td>100.00</td>
<td>72.47</td>
<td>94.81</td>
</tr>
<tr>
<td>pmm</td>
<td>Thick bar</td>
<td>99.71</td>
<td>62.94</td>
<td>86.85</td>
</tr>
<tr>
<td>pmm</td>
<td>Netting multiple</td>
<td>22.35</td>
<td>63.70</td>
<td>66.05</td>
</tr>
<tr>
<td>pmm</td>
<td>Knots</td>
<td>100.00</td>
<td>62.57</td>
<td>96.30</td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td></td>
<td>74.67</td>
<td>69.08</td>
<td>84.45</td>
</tr>
<tr>
<td>p2</td>
<td>Broken end</td>
<td>74.69</td>
<td>81.13</td>
<td>95.55</td>
</tr>
<tr>
<td>p2</td>
<td>Hole</td>
<td>40.03</td>
<td>94.58</td>
<td>79.75</td>
</tr>
<tr>
<td>p2</td>
<td>Thin bar</td>
<td>91.48</td>
<td>96.67</td>
<td>97.94</td>
</tr>
<tr>
<td>p2</td>
<td>Thick bar</td>
<td>89.35</td>
<td>88.69</td>
<td>96.00</td>
</tr>
<tr>
<td>p2</td>
<td>Netting multiple</td>
<td>56.76</td>
<td>74.82</td>
<td>82.21</td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td></td>
<td>70.46</td>
<td>87.18</td>
<td>90.29</td>
</tr>
<tr>
<td>p4m</td>
<td>Broken end</td>
<td>78.46</td>
<td>74.83</td>
<td>92.56</td>
</tr>
<tr>
<td>p4m</td>
<td>Hole</td>
<td>17.26</td>
<td>63.54</td>
<td>72.78</td>
</tr>
<tr>
<td>p4m</td>
<td>Thin bar</td>
<td>36.41</td>
<td>84.24</td>
<td>61.64</td>
</tr>
<tr>
<td>p4m</td>
<td>Thick bar</td>
<td>100.00</td>
<td>90.00</td>
<td>99.50</td>
</tr>
<tr>
<td>p4m</td>
<td>Netting multiple</td>
<td>10.02</td>
<td>39.92</td>
<td>65.78</td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td></td>
<td>48.43</td>
<td>70.51</td>
<td>78.45</td>
</tr>
</tbody>
</table>
4.3.1.5 Conclusion

The following can be concluded from the proposed method of defect detection based on Gabor wavelets:

(i) Texture-periodicity has been effectively utilized for determining the size of the Gabor kernels for each test image and for defect detection in Gabor-space using hierarchical clustering.

(ii) It is very clear that defects are highly enhanced in Gabor-space. The intensities of the defective zones are higher than those of the non-defective zones in Gabor-space as if the defects are easily identifiable by human vision system in the spatial-domain of the original image.

(iii) In the absence of false positive, fusion of defects identified from four cropped images generated from the input image helps in getting an overview of the total defects.

4.3.2 HVP contrast based method

4.3.2.1 Introduction

Textural features corresponding to human visual perception are very useful for optimum feature selection and texture analyzer design (Tamura et al., 1978). Tamura et al. developed six features, viz., coarseness, contrast, directionality, line-likeness, regularity, and roughness, in accordance with psychological studies on the human perception of textures with the help of 16 natural texture images from Brodatz album (1966) and described the properties as follows:

(i) **Coarseness** - Coarseness is the most fundamental textural feature and can be considered as a measure of granularity of a texture. In the narrow sense, the texture means the coarseness. When two texture patterns differ from each other only in scale, the magnified one is coarser. For patterns with different structures, the bigger its element size and/or the less its elements are repeated, the coarser it is felt to be. To calculate coarseness of an image \( g(x, y) \), moving averages \( A_k(x, y) \) are first computed using \( 2^k \times 2^k \) \( (k = 0, 1, \ldots, 5) \) size windows at each pixel \( (x, y) \) as

\[
A_k(x, y) = \sum_{i=x-2^k}^{x+2^k-1} \sum_{j=y-2^k}^{y+2^k-1} g(i, j) / 2^{2k}
\]

(4.6)
Then, the differences between pairs of non-overlapping moving averages in the horizontal and vertical directions of each pixel are calculated as

\[ E_{k,x}(x, y) = \left| A_k(x + 2^{k-1}, y) - A_k(x - 2^{k-1}, y) \right| \]

\[ E_{k,y}(x, y) = \left| A_k(x, y + 2^{k-1}) - A_k(x, y - 2^{k-1}) \right| \]

Afterwards, the value of \( k \) that maximizes \( E \) in either direction is used to set the best size for each pixel as

\[ S_{\text{best}}(x, y) = 2^k \]

The coarseness is then computed by averaging \( S_{\text{best}} \) over the entire image as

\[ F_{\text{crs}} = \frac{1}{m \times n} \sum_{i=1}^{m} \sum_{j=1}^{n} S_{\text{best}}(i, j) \]

(ii) **Contrast** - In visual perception of the real-world, contrast is the difference in visual properties that makes an object in an image distinguishable from other objects and the background of the image. Contrast aims to capture the dynamic range of gray levels in an image together with polarization of the distribution of black and white pixels. Standard deviation (\( \sigma \)) in an image is a measure of the dynamic range of gray levels and the kurtosis (\( \alpha_4 \)) is a measure of polarization of the distribution of black and white pixels. Combining these two measures, contrast is defined as

\[ F_{\text{con}} = \lambda \sigma^4 \left( \alpha_4 \right)^{3/4} \]

where \( \lambda \) is a constant. It was experimentally observed that \( \lambda = 0.25 \) yields best correlation between the computational measurements and the psychological experiments. The kurtosis is given by

\[ \alpha_4 = \frac{\mu_4}{\sigma^4} \]

The fourth moment about the mean (\( \mu_4 \)) and standard deviation of the histogram (\( \sigma \)) are given by

\[ \mu_4 = \sum_{k=0}^{L-1} (\bar{r} - r_k)^4 p(r_k) \]

\[ \sigma = \sqrt{\sum_{k=0}^{L-1} (\bar{r} - r_k)^2 p(r_k)} \]

where, \( \bar{r} \) is the average intensity given by

\[ \bar{r} = \sum_{k=0}^{L-1} r_k p(r_k) \]

\( p(r_k) \) is the probability of occurrence of gray level \( r_k \) given by

\[ p(r_k) = \frac{n_k}{n}, \; k = 0, 1, \cdots, L-1 \]
where $n$ is the total number of pixels in a periodic block, $n_k$ is the number of pixels that have gray level $r_k$, and $L$ is the total number of gray values.

(iii) **Directionality** - It is known that directionality in an original picture can be preserved in its Fourier power spectrum. We can find the directionality in the histogram of the Fourier power along lines through the origin. However, it seems uneconomical to compute the time-consuming Fourier transform only for directionality and no other feature can be extracted from Fourier power spectrum. Therefore, it is desirable to use a faster procedure in spatial domain. Instead of a histogram of Fourier power, histogram of local edge probabilities against their directional angle can be utilized. To compute the directionality, image is convoluted with two $3 \times 3$ arrays as follows:

$$
\begin{bmatrix}
  -1 & 0 & 1 \\
  -1 & 0 & 1 \\
  -1 & 0 & 1 \\
\end{bmatrix}
&
\begin{bmatrix}
  1 & 1 & 1 \\
  0 & 0 & 0 \\
  -1 & -1 & -1 \\
\end{bmatrix}
$$

A gradient vector is computed whose magnitude and angle are defined as

$$
|\Delta G| = \sqrt{\Delta_H^2 + \Delta_V^2} \quad (4.17)
$$

$$
\theta = \tan^{-1}\left(\frac{\Delta_V}{\Delta_H}\right) + \pi/2 \quad (4.18)
$$

where $\Delta_H$ and $\Delta_V$ are the horizontal and vertical differences of the convolution. Then by quantizing $\theta$ and counting the pixels with corresponding magnitude larger than a threshold, a histogram of $\theta$, denoted as $H_{D\theta}$, can be constructed. This histogram will exhibit strong peaks for highly directional textures and will be relatively flat for other images without strong orientation. The entire histogram is then summated to obtain an overall directionality measure based on the sharpness of the peaks as

$$
F_{dir} = \sum_p \sum_{\phi \in w_p} H_D(\phi) \quad (4.19)
$$

In this, sum $p$ ranges over $n_p$ peaks; and for each peak $p$, $w_p$ is the set of bins distributed over it; while $\phi_p$ is the bin that takes the peak value.

(iv) **Line-likeness** - Line-likeness is viewed as an element of texture that is composed of lines. Hence, when the direction and the neighboring (edge's) direction for a given edge are nearly equal, such a group of edge points is regarded as a line. As a measure of line-likeness, the following measure is defined so that co-occurrences in the same direction are weighted by +1 and those in the perpendicular direction by −1:
where $P_D$ is the $n \times n$ local direction co-occurrence matrix.

(v) **Regularity** - For highly regular patterns, some techniques may be used to indicate that they are regular. However, for natural textures which are difficult to describe mathematically, it is fairly difficult to measure a degree of irregularity without any information such as element size or shape. Hence, it is assumed that if any feature of a texture varies over the whole image, the image is irregular. Partitioned subimages are taken and the variation of each feature is considered in each subimage. Sum of the variation for each of these four features is taken as a measure of regularity and calculated as

$$F_{\text{reg}} = 1 - r \left( \sigma_{\text{crs}} + \sigma_{\text{con}} + \sigma_{\text{dir}} + \sigma_{\text{lin}} \right)$$  \hspace{1cm} (4.21)$$

where $r$ is the normalizing factor and each $\sigma_{xx}$ is the standard deviation of $F_{xx}$.

(vi) **Roughness** – Roughness is approximated as the summation of coarseness and contrast.

Having defined these six features, Tamura et al. conducted psychological experiments on human subjects consisting of 28 men and 20 women. In advance of the experiments, a brief explanation of the basic concept of texture and the six features were explained to them. Each of them was given 16 Brodatz textures (viz., D3, D9, D15, D20, D28, D33, D34, D38, D67, D68, D69, D84, D93, D98, D109, D111) and asked to arrange the textures for each feature from minimum to maximum (i.e., least coarseness to highest coarseness, least contrast to highest contrast, etc.). All measures were computed separately for each Brodatz texture image. In order to compare the computational values against the psychological results, Pearson’s correlation coefficient was used. The correlation coefficients obtained for coarseness, contrast, directionality, line-likeness, regularity, and roughness were 0.831, 0.904, 0.823, 0.713, 0.779 and 0.653, respectively. Out of all six features, contrast yielded the highest correlation coefficient. This could possibly be due to the fact that human visual system is more sensitive to contrast than absolute luminance. As a result, one can perceive the world similarly regardless of the huge changes in illumination over the day or from place to place (Eli, 1990).
4.3.2.2 Proposed method

Though all six texture features yield very good results with reference to psychological experiments, once a periodically patterned image is split into several blocks of size same as that of a periodic block, the three features - coarseness, directionality and regularity become no longer valid. Among the rest three features (contrast, line-likeness and roughness), line-likeness strictly depends on directionality which has no significance once a periodic texture is split into several periodic blocks and roughness is more meaningful for stochastic textures only. The feature – contrast has the highest rank correlation with reference to psychological experiments conducted by Tamura et al. (1978). Hence, contrast can be regarded as the best measure for the present defect detection study considering its significance from the psycho-computational experiments of Tamura et al. (1978). As this contrast measure is based on human vision perception (HVP), we call the contrast measure used in our present study as HVP based contrast. Presence of defect in a periodic block of an image will have difference in HVP based contrast with reference to the neighboring periodic blocks and hence a feature vector can be formed using HVP based contrast from the periodic blocks for defect detection. In addition to this local contrast, the absolute deviation of the contrast of a periodic block with reference to global contrast is taken as a discriminating factor and another feature vector is formed using this absolute deviation as

\[ \delta_i = |F_{con_i} - F_{con_{global}}| \]  (4.22)

The HVP based local contrast and its absolute deviation with respect to global contrast together form a 2-dimensional feature space for the defect detection.

4.3.2.3 Illustration of the proposed method

In order to illustrate the proposed method of defect detection, let us consider the sample defective image (p4m image with thick bar defect – tt6) as shown in Fig. 4.15. As suggested in the previous method, four cropped images are obtained from the test image and each cropped is split into several periodic blocks. Both local HVP contrast (ie., HVP contrast calculated from periodic block) and the absolute deviation between local contrast and global contrast are calculated and used as 2-dimensional feature space. For the sample test image, the dissimilarity measures calculated from both features using Euclidean norm for all four cropped images are shown in gray
Each dissimilarity matrix is subjected to Ward’s hierarchical clustering to get two clusters and the defective cluster is identified based on number of periodic blocks in each cluster. Fig. 4.109 shows the result of cluster analysis in the form of dendrograms and Fig. 4.110 shows the identified defective blocks for each cropped image. Here also, in the absence of false positives, we can employ the concept of defect-fusion as explained in the defect detection method based on Gabor wavelets. The result of defect fusion for the test image used in HVP is shown in Fig. A.2 in Appendix-I.

**Fig. 4.108 :** Dissimilarity matrix obtained using HVP contrasts from (a) top-left (b) bottom-left (c) top-right (d) bottom-right corners of the test image shown in gray scale.
Fig. 4.109: Result of cluster analysis showing dendrograms of each dissimilarity matrix obtained using HVP contrasts from (a) top-left (b) bottom-left (c) top-right (d) bottom-right corners of the test image.

Fig. 4.110: Defective periodic blocks identified from the cropped image obtained from (a) top-left (b) bottom-left (c) top-right (d) bottom-right corners of the test image using HVP contrasts.
4.3.2.4 Experimental analysis

Defective images from all three major wallpaper groups are tested using the method of HVP contrasts and the performance measures are given in Table-4.3.

Table-4.3: Performance parameters for HVP contrast based method of defect detection

<table>
<thead>
<tr>
<th>Wallpaper group</th>
<th>Defect</th>
<th>Precision (%)</th>
<th>Recall (%)</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>pmm</td>
<td>Broken end</td>
<td>98.59</td>
<td>100.00</td>
<td>99.76</td>
</tr>
<tr>
<td>pmm</td>
<td>Hole</td>
<td>100.00</td>
<td>74.40</td>
<td>96.67</td>
</tr>
<tr>
<td>pmm</td>
<td>Thin bar</td>
<td>100.00</td>
<td>65.83</td>
<td>96.35</td>
</tr>
<tr>
<td>pmm</td>
<td>Thick bar</td>
<td>100.00</td>
<td>93.64</td>
<td>98.02</td>
</tr>
<tr>
<td>pmm</td>
<td>Netting multiple</td>
<td>22.35</td>
<td>46.50</td>
<td>74.05</td>
</tr>
<tr>
<td>pmm</td>
<td>Knots</td>
<td>80.63</td>
<td>74.75</td>
<td>91.67</td>
</tr>
</tbody>
</table>

| Average         |               | 83.60         | 75.85      | 92.75        |
| p2              | Broken end    | 52.34         | 90.63      | 90.96        |
| p2              | Hole          | 46.36         | 93.33      | 86.25        |
| p2              | Thin bar      | 82.42         | 90.00      | 95.16        |
| p2              | Thick bar     | 82.04         | 87.22      | 96.77        |
| p2              | Netting multiple | 39.11   | 88.57      | 85.89        |

| Average         |               | 60.45         | 89.95      | 91.01        |
| p4m             | Broken end    | 48.43         | 58.84      | 84.26        |
| p4m             | Hole          | 11.10         | 60.00      | 72.06        |
| p4m             | Thin bar      | 50.64         | 70.95      | 84.33        |
| p4m             | Thick bar     | 80.08         | 75.83      | 92.92        |
| p4m             | Netting multiple | 13.03   | 40.95      | 74.50        |

| Average         |               | 40.66         | 61.32      | 81.61        |

4.3.2.5 Conclusion

The following can be concluded from the proposed method of defect detection based on HVP contrasts:

(i) Two HVP based measures of contrast, *viz.*, local contrast and absolute deviation between local contrast and global contrast have been effectively used for capturing defective periodic blocks.

(ii) The method is based on simple first order statistics. However, the performance of the proposed algorithm is like human vision system.
(iii) In the absence of false positive, fusion of defects identified from four cropped images generated from the input image helps in getting an overview of the total defects.

4.4 Defect detection methods based on non-HVP

Among various texture analysis methods, methods involving simple statistical features can also be thought of as appropriate features for finding texture defects. The first order statistics involving histogram features are quite common in various texture analysis applications. Though these measures are not necessarily HVP based, these can be effectively utilized for defect detection in textures. In this section, we propose three different methods utilizing first order statistical features. The first method is chi-square distance based method, the second one is Jensen-Shannon divergence based method and the third one is the method based on Universal Quality Index.

The chi-square distance and the Jensen-Shannon divergence measures are dissimilarity or distance measures for discriminating two probabilities. Though several distance measures exist, we chose these two measures for defect detection based on their simplicity, true-metrics and discriminating capability. The chi-square distance is one of the powerful measures for better discrimination between two histograms, and has its origin from chi-square statistics used to test the best fit between a distribution (Pele and Werman, 2010). Jensen-Shannon divergence is one of the effective measures for capturing mutual information between two probability distributions (Endres and Schindelin, 2003).

Universal Quality Index is a measure of loss of correlation, luminance distortion and contrast distortion between any two signals and was proposed by Wang and Bovik (2002). When a defect present in a texture differs in correlation, luminance and contrast in relation to the defect-free portions, the method based on universal quality index is very effective. Given several defective textures, one can easily categorize which defect has the highest deviation and which has the least deviation in all these three measures.
4.4.1 Chi-square distance based method

4.4.1.1 Introduction

The chi-square measure is one of the powerful measures for better discrimination between two histograms and has been widely used in various applications such as texture and object categories classification, shape matching, shape classification and boundary detection. In histograms of many processes, the difference between large bins is less important than the difference between small bins and should be reduced for better discrimination between two histograms. The chi-square histograms take this into account (Pele and Werman, 2010). In fact, the chi-square histogram distance comes from the chi-square statistics used to test the best fit between a distribution and observed frequencies. If \( p \) and \( q \) represent first order histograms of two different images \( A \) and \( B \) of size \( M \times N \), the chi-square measure between these two histograms is given by

\[
\chi^2(p, q) = \frac{1}{2} \sum_{k=0}^{L-1} \left( p(r_k) - q(r_k) \right)^2 \left( p(r_k) + q(r_k) \right) \tag{4.23}
\]

The first order histograms are given as

\[
p(r_k) = \frac{n_{A,i}}{n}, \quad q(r_k) = \frac{n_{B,i}}{n}, \quad i = 0, 1, 2, \ldots, L-1 \tag{4.24}
\]

where \( n_{A,i} \) is the number of pixels that have gray level \( r_k \) in the image \( A \), \( n_{B,i} \) is the number of pixels that have gray level \( r_k \) in the image \( B \), \( n \) is the total number of pixels in the image \( A \) or \( B \), and \( L \) is the total number of gray values in the image \( A \) or \( B \). The square root of chi-square measure is a distance metric (Pele and Werman, 2010) which is termed here as \( \text{Chi-square Histogram Distance} \chi \).

4.4.1.2 Proposed method

Each cropped image is split into several periodic blocks and the distance metrics based on chi-square measures are calculated for each periodic block with respect to itself and all other periodic blocks to get a distance matrix (dissimilarity matrix). If a cropped image has \( n_p \) number of periodic blocks, then the dissimilarity matrix is a square matrix of size \( n_p \times n_p \) as given below:

\[
\chi^2(p, q) = \frac{1}{2} \sum_{k=0}^{L-1} \left( p(r_k) - q(r_k) \right)^2 \left( p(r_k) + q(r_k) \right) \tag{4.23}
\]

\[
p(r_k) = \frac{n_{A,i}}{n}, \quad q(r_k) = \frac{n_{B,i}}{n}, \quad i = 0, 1, 2, \ldots, L-1 \tag{4.24}
\]
Since $\chi$ of a periodic block with itself is zero and $\chi$ between $i^{th}$ periodic block and $j^{th}$ periodic block is same as $\chi$ between $j^{th}$ periodic block and $i^{th}$ periodic block, the dissimilarity matrix becomes a diagonally symmetric matrix with diagonal elements being zero (hollow matrix) as below:

$$\Psi = \begin{bmatrix}
\chi_{1,1} & \chi_{1,2} & \cdots & \chi_{1,n_p-1} & \chi_{1,n_p} \\
\chi_{2,1} & \chi_{2,2} & \cdots & \chi_{2,n_p-1} & \chi_{2,n_p} \\
& \vdots & \ddots & \vdots \\
\chi_{n_p-1,1} & \chi_{n_p-1,2} & \cdots & \chi_{n_p-1,n_p-1} & \chi_{n_p-1,n_p} \\
\chi_{n_p,1} & \chi_{n_p,2} & \cdots & \chi_{n_p,n_p-1} & \chi_{n_p,n_p}
\end{bmatrix}$$

(4.25)

It may be noted that the upper diagonal elements are not filled for the sake of simplicity. This dissimilarity matrix is subjected to Ward’s hierarchical clustering to identify defective and defect-free clusters.

### 4.4.1.3 Illustration of the proposed method

In order to illustrate the proposed method of defect detection, let us consider the same defective image (p4m image with thick bar defect – tt6) as shown in Fig. 4.15. As suggested in the previous methods, four cropped images are obtained from the test image and symmetric dissimilarity matrices containing chi-square distance metrics are calculated for each cropped image. The dissimilarity matrices for all four cropped images are shown in gray scale in Fig. 4.111. Each dissimilarity matrix is subjected to Ward’s hierarchical clustering to get two clusters and the defective cluster is identified based on number of periodic blocks in each cluster. Fig. 4.112 shows the result of cluster analysis in the form of dendrograms and Fig. 4.113 shows the identified defects for each cropped image. Here also, in the absence of false positives, we can employ the concept of defect-fusion as explained in the HVP based methods. The result of defect fusion for the test image used for algorithm demonstration is shown in Fig. A.3 in Appendix-I.
Fig. 4.111: Dissimilarity matrix derived from the chi-square distance metrics for the cropped image obtained from (a) top-left (b) bottom-left (c) top-right and (d) bottom-right corners of the test image shown in gray-scale.

Fig. 4.112: Dendrograms obtained from cluster analysis of the chi-square distance matrix obtained from the test image by cropping it from (a) top-left (b) bottom-left (c) top-right and (d) bottom-right-right corners. It may be noted that since the cropped images have more number of periodic blocks, the identities of the periodic blocks in the abscissa are not shown in order to avoid crowd and to have better clarity.
Defective periodic blocks identified from the cluster analysis of dissimilarity matrix derived from the chi-square distance measure of the cropped images obtained from (a) top-left (b) bottom-left (c) top-right and (d) bottom-right corners of the test image with their boundaries highlighted using white pixels.

### 4.4.1.4 Experimental analysis

Defective images from all three major wallpaper groups are tested using the method of chi-square distance and the performance measures are given in Table-4.4.

#### Table-4.4: Performance parameters for chi-square distance based method of defect detection

<table>
<thead>
<tr>
<th>Wallpaper group</th>
<th>Defect</th>
<th>Precision (%)</th>
<th>Recall (%)</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>pmm</td>
<td>Broken end</td>
<td>97.48</td>
<td>98.46</td>
<td>99.21</td>
</tr>
<tr>
<td>pmm</td>
<td>Hole</td>
<td>100.00</td>
<td>84.76</td>
<td>97.94</td>
</tr>
<tr>
<td>pmm</td>
<td>Thin bar</td>
<td>100.00</td>
<td>83.69</td>
<td>98.25</td>
</tr>
<tr>
<td>pmm</td>
<td>Thick bar</td>
<td>100.00</td>
<td>91.10</td>
<td>96.98</td>
</tr>
<tr>
<td>pmm</td>
<td>Netting multiple</td>
<td>73.63</td>
<td>95.41</td>
<td>91.27</td>
</tr>
<tr>
<td>pmm</td>
<td>Knots</td>
<td>93.91</td>
<td>96.67</td>
<td>98.25</td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td></td>
<td><strong>94.17</strong></td>
<td><strong>91.68</strong></td>
<td><strong>96.98</strong></td>
</tr>
<tr>
<td>p2</td>
<td>Broken end</td>
<td>36.76</td>
<td>59.71</td>
<td>83.26</td>
</tr>
<tr>
<td>p2</td>
<td>Hole</td>
<td>3.01</td>
<td>47.02</td>
<td>65.26</td>
</tr>
<tr>
<td>p2</td>
<td>Thin bar</td>
<td>40.83</td>
<td>46.07</td>
<td>77.40</td>
</tr>
<tr>
<td>p2</td>
<td>Thick bar</td>
<td>61.28</td>
<td>67.90</td>
<td>86.93</td>
</tr>
<tr>
<td>p2</td>
<td>Netting multiple</td>
<td>42.62</td>
<td>61.55</td>
<td>72.86</td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td></td>
<td><strong>36.90</strong></td>
<td><strong>56.45</strong></td>
<td><strong>77.14</strong></td>
</tr>
<tr>
<td>p4m</td>
<td>Broken end</td>
<td>75.09</td>
<td>88.00</td>
<td>89.83</td>
</tr>
<tr>
<td>p4m</td>
<td>Hole</td>
<td>4.88</td>
<td>75.00</td>
<td>58.95</td>
</tr>
<tr>
<td>p4m</td>
<td>Thin bar</td>
<td>36.98</td>
<td>83.33</td>
<td>78.06</td>
</tr>
<tr>
<td>p4m</td>
<td>Thick bar</td>
<td>91.07</td>
<td>90.13</td>
<td>98.39</td>
</tr>
<tr>
<td>p4m</td>
<td>Netting multiple</td>
<td>18.52</td>
<td>72.76</td>
<td>73.59</td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td></td>
<td><strong>45.31</strong></td>
<td><strong>81.84</strong></td>
<td><strong>79.76</strong></td>
</tr>
</tbody>
</table>
4.4.1.5 Conclusion

The following can be concluded from the proposed method of defect detection based on chi-square distance:

(i) The method is based on simple first order statistics.
(ii) Chi-square distance metric can be effectively used in conjunction with periodicity for discriminating defective and defect-free classes.
(iii) In the absence of false positive, fusion of defects identified from four cropped images generated from the input image helps in getting an overview of the total defects.

4.4.2 Jensen-Shannon divergence based method

4.4.2.1 Introduction

Jensen-Shannon divergence is one of the effective measures for capturing mutual information between two probability distributions (Endres and Schindelin, 2003). Jensen-Shannon divergence is a symmetrized and smoothed version of Kullback-Leibler divergence which is the most important divergence measure of information theory (Endres and Schindelin, 2003). Given two classes $\omega_1$ and $\omega_2$ with a common feature vector $x$, the Kullback-Leibler divergence or the relative entropy in terms of ratio of the probability distributions $p(\omega_1)$ and $p(\omega_2)$ of these classes conveys useful information concerning the capability of discriminating the two classes. This class-separability measure over class $\omega_1$ is given as (Theodoridis and Koutroumbas, 2009)

$$\lambda(\omega_1, \omega_2) = \int_{-\infty}^{\infty} p(\omega_1) \log \left( \frac{p(\omega_1)}{p(\omega_2)} \right) dx$$

(4.27)

Similarly, the class-separability measure over class $\omega_2$ is given as

$$\lambda(\omega_2, \omega_1) = \int_{-\infty}^{\infty} p(\omega_2) \log \left( \frac{p(\omega_2)}{p(\omega_1)} \right) dx$$

(4.28)

Based on the probability distributions $p(\omega_1)$ and $p(\omega_2)$ and their average, a symmetric divergence called Jensen-Shannon divergence ($\Lambda$) is given as

---

\[
\Lambda = \int_{-\infty}^{\infty} \left[ p(\omega_1) \log \left( \frac{0.5 \times p(\omega_1)}{p(\omega_1) + p(\omega_2)} \right) + p(\omega_2) \log \left( \frac{0.5 \times p(\omega_2)}{p(\omega_1) + p(\omega_2)} \right) \right] dx
\]

(4.29)

Since the Kullback-Leibler divergence \( \lambda(\omega_1, \omega_2) \) or \( \lambda(\omega_2, \omega_1) \) can be interpreted as the inefficiency of assuming that the true distribution is \( p(\omega_2) \) or \( p(\omega_1) \) when it is really \( p(\omega_1) \) or \( p(\omega_2) \), the Jensen-Shannon divergence could be seen as a minimum inefficiency distance (Endres and Schindelin, 2003). The square-root of this divergence is a true metric obeying the following properties of a true metric in 2D Euclidean-space:

(i) Non-negativity \( (\Lambda_{ij} > 0) \), for all \( i \) and \( j \)

(ii) Self-distance \( (\Lambda_{ii} = 0) \), if \( i = j \)

(iii) Symmetry \( (\Lambda_{ij} = \Lambda_{ji}) \) for all \( i \) and \( j \)

(iv) Triangular-inequality \( (\sqrt{\Lambda_{ik}} \leq \sqrt{\Lambda_{ij}} + \sqrt{\Lambda_{jk}}) \) for \( i \neq j \neq k \)

If \( p \) and \( q \) represent the probability distributions of two periodic blocks \( A \) and \( B \) whose dynamic range of gray values is \([0, L-1]\), the Jensen-Shannon divergence can be computed as (Endres and Schindelin, 2003)

\[
\Lambda_{A,B} = \Lambda_{B,A} = \sum_{k=0}^{L-1} p(r_k) \log \left( \frac{0.5 \times p(r_k)}{p(r_k) + q(r_k)} \right) + \sum_{k=0}^{L-1} q(r_k) \log \left( \frac{0.5 \times q(r_k)}{p(r_k) + q(r_k)} \right)
\]

(4.30)

where the probability distributions of the two periodic blocks \( A \) and \( B \) are given by

\[
p(r_k) = \frac{n_{A,i}}{n}, \quad q(r_k) = \frac{n_{B,i}}{n}, \quad i = 0, 1, 2, \ldots, L-1
\]

(4.31)

where \( n_{A,i} \) is the number of pixels that have gray level \( r_k \) in the image \( A \), \( n_{B,i} \) is the number of pixels that have gray level \( r_k \) in the image \( B \), \( n \) is the total number of pixels in the image \( A \) or \( B \), and \( L \) is the total number of gray values in the periodic block \( A \) or \( B \).

### 4.4.2.2 Proposed method

Similar to the previous methods, each cropped image is split into \( n_p \) number of periodic blocks. The Jensen-Shannon divergence metrics are calculated for each periodic block with respect to itself and all other periodic blocks to get a dissimilarity matrix. For a cropped image with \( n_p \) number of periodic blocks, the dissimilarity matrix of size \( n_p \times n_p \) is given as
Because the divergence measure of a periodic block with itself is zero and the divergence measure between $i^{th}$ periodic block and $j^{th}$ periodic block is same as the divergence measure between $j^{th}$ periodic block and $i^{th}$ periodic block, the dissimilarity matrix becomes a diagonally symmetric matrix with diagonal elements being zero (hollow matrix) as below:

$$D = \begin{bmatrix}
\sqrt{A_{1,1}} & \sqrt{A_{1,2}} & \cdots & \sqrt{A_{1,n_p-1}} & \sqrt{A_{1,n_p}} \\
\sqrt{A_{2,1}} & \sqrt{A_{2,2}} & \cdots & \sqrt{A_{2,n_p-1}} & \sqrt{A_{2,n_p}} \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
\sqrt{A_{n_p-1,1}} & \sqrt{A_{n_p-1,2}} & \cdots & \sqrt{A_{n_p-1,n_p-1}} & \sqrt{A_{n_p-1,n_p}} \\
\sqrt{A_{n_p,1}} & \sqrt{A_{n_p,2}} & \cdots & \sqrt{A_{n_p,n_p-1}} & \sqrt{A_{n_p,n_p}}
\end{bmatrix} \quad (4.32)$$

It may be noted that the upper diagonal elements are not filled for the sake of simplicity. This dissimilarity matrix is subjected to Ward’s hierarchical clustering to identify defective and defect-free clusters.

### 4.4.2.3 Illustration of the proposed method

In order to illustrate the proposed method of defect detection, let us consider the same defective image (p4m image with thick bar defect – tt6) as shown in Fig. 4.15. As suggested in the previous methods, four cropped images are obtained from the test image and symmetric dissimilarity matrices containing Jensen-Shannon divergence metrics are calculated for each cropped image. The dissimilarity matrices calculated based on Jensen-Shannon divergence metrics for all four cropped images are shown in gray scale in Fig. 4.114. Each dissimilarity matrix is subjected to Ward’s hierarchical clustering to get two clusters and the defective cluster is identified based on number of periodic blocks in each cluster. Fig. 4.115 shows the result of cluster analysis in the form of dendrograms and Fig. 4.116 shows the identified defects for each cropped image. Here also, in the absence of false positives, we can employ the concept of defect-fusion as explained in other methods. The result of defect fusion for the test image used for algorithm demonstration is shown in Fig. A.4 in Appendix-I.
Fig. 4.14: Dissimilarity matrix derived from the Jensen-Shannon divergence measures for the cropped image obtained from (a) top-left (b) bottom-left (c) top-right and (d) bottom-right corners of the test image shown in gray-scale.

Fig. 4.15: Dendrograms obtained from cluster analysis of the Jensen-Shannon divergence matrix obtained from the test image by cropping it from (a) top-left (b) bottom-left (c) top-right and (d) bottom-right corners. It may be noted that since the cropped images have more number of periodic blocks, the identities of the periodic blocks in the abscissa are not shown in order to avoid crowd and to have better clarity.
Fig. 4.16: Defective periodic blocks identified from the cluster analysis of dissimilarity matrix derived from the Jensen-Shannon divergence measure of the cropped images obtained from (a) top-left (b) bottom-left (c) top-right and (d) bottom-right corners of the test image with their boundaries highlighted using white pixels.

4.4.2.4 Experimental analysis

Defective images from all three major wallpaper groups are tested using the method of Jensen-Shannon divergence and the performance measures are given in Table 4.5.

Table 4.5: Performance parameters for Jensen-Shannon divergence based method of defect detection

<table>
<thead>
<tr>
<th>Wallpaper group</th>
<th>Defect</th>
<th>Precision (%)</th>
<th>Recall (%)</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>pmm</td>
<td>Broken end</td>
<td>97.89</td>
<td>99.38</td>
<td>99.44</td>
</tr>
<tr>
<td>pmm</td>
<td>Hole</td>
<td>100.00</td>
<td>88.10</td>
<td>98.57</td>
</tr>
<tr>
<td>pmm</td>
<td>Thin bar</td>
<td>60.00</td>
<td>50.33</td>
<td>86.35</td>
</tr>
<tr>
<td>pmm</td>
<td>Thick bar</td>
<td>100.00</td>
<td>91.10</td>
<td>96.98</td>
</tr>
<tr>
<td>pmm</td>
<td>Netting multiple</td>
<td>75.66</td>
<td>93.61</td>
<td>92.06</td>
</tr>
<tr>
<td>pmm</td>
<td>Knots</td>
<td>80.00</td>
<td>76.43</td>
<td>96.43</td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td></td>
<td>85.59</td>
<td>83.16</td>
<td>94.97</td>
</tr>
<tr>
<td>p2</td>
<td>Broken end</td>
<td>41.52</td>
<td>81.19</td>
<td>81.15</td>
</tr>
<tr>
<td>p2</td>
<td>Hole</td>
<td>1.53</td>
<td>21.13</td>
<td>64.65</td>
</tr>
<tr>
<td>p2</td>
<td>Thin bar</td>
<td>42.36</td>
<td>57.32</td>
<td>79.01</td>
</tr>
<tr>
<td>p2</td>
<td>Thick bar</td>
<td>61.08</td>
<td>68.24</td>
<td>85.16</td>
</tr>
<tr>
<td>p2</td>
<td>Netting multiple</td>
<td>20.34</td>
<td>38.78</td>
<td>74.95</td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td></td>
<td>33.37</td>
<td>53.33</td>
<td>76.98</td>
</tr>
<tr>
<td>p4m</td>
<td>Broken end</td>
<td>53.06</td>
<td>76.25</td>
<td>81.04</td>
</tr>
<tr>
<td>p4m</td>
<td>Hole</td>
<td>3.53</td>
<td>36.98</td>
<td>59.17</td>
</tr>
<tr>
<td>p4m</td>
<td>Thin bar</td>
<td>37.35</td>
<td>79.45</td>
<td>77.82</td>
</tr>
<tr>
<td>p4m</td>
<td>Thick bar</td>
<td>86.16</td>
<td>90.13</td>
<td>94.22</td>
</tr>
<tr>
<td>p4m</td>
<td>Netting multiple</td>
<td>15.46</td>
<td>62.75</td>
<td>69.33</td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td></td>
<td>39.11</td>
<td>69.11</td>
<td>76.32</td>
</tr>
</tbody>
</table>
4.4.2.5 Conclusion

The following can be concluded from the proposed method of defect detection based on Jensen-Shannon divergence:

(i) The method is based on simple first order statistics.
(ii) Jensen-Shannon divergence metric can be effectively used in conjunction with periodicity for discriminating defective and defect-free classes.
(iii) In the absence of false positive, fusion of defects identified from four cropped images generated from the input image helps in getting an overview of the total defects.

4.4.3 Universal quality index based method

4.4.3.1 Introduction

Universal quality index is a measure of loss of correlation, luminance distortion and contrast distortion between any two signals (Wang and Bovik, 2002). Defective zones of a patterned texture will differ in correlation, luminance or contrast with respect to that of defect-free zones of the texture. Hence, defective zones can be easily identified using the concept of universal quality index. According to Wang and Bovik (2002), the universal quality index (UQI) which is a measure of similarity between two signals \( x = \{ x_i | i = 1, 2, \cdots, N \} \) and \( y = \{ y_i | i = 1, 2, \cdots, N \} \) is given by

\[
q_{x,y} = \frac{4\sigma_{xy} \bar{xy}}{\sigma_x^2 + \sigma_y^2 (\bar{x}^2 + \bar{y}^2)}
\]  

(4.34)

where

\[
\bar{x} = \frac{1}{N} \sum_{i=1}^{N} x_i, \quad \bar{y} = \frac{1}{N} \sum_{i=1}^{N} y_i, \quad \sigma_{xy} = \frac{1}{N-1} \sum_{i=1}^{N} (x_i - \bar{x})(y_i - \bar{y})
\]

\[
\sigma_x^2 = \frac{1}{N-1} \sum_{i=1}^{N} (x_i - \bar{x})^2, \quad \sigma_y^2 = \frac{1}{N-1} \sum_{i=1}^{N} (y_i - \bar{y})^2
\]  

(4.35)

The quality index equation can be rearranged and written as

\[
q_{x,y} = \frac{\sigma_{xy}}{\sigma_x \sigma_y} \cdot \frac{2\bar{xy}}{\bar{x}^2 + \bar{y}^2} \cdot \frac{2\sigma_x \sigma_y}{\sigma_x^2 + \sigma_y^2}
\]  

(4.36)

\(^\dagger\) The proposed method of defect detection based on Universal Quality Index has been presented in the 5th Indian International conference on Artificial Intelligence (IICAI-2011) held at Tumkur, India, during 14-16 December 2011, under the title “Unsupervised Detection of Texture Defects using Texture-Periodicity and Universal Quality Index.”

This paper also appears as a part of full paper under the title “Automatic Detection of Defects on Periodically Patterned Textures,” in Journal of Intelligent Systems, Vol. 20, No. 3, 279-303, 2011.
The first component in the equation is the correlation coefficient between the two signals that measures the degree of correlation between the two signals and its dynamic range is (-1, 1). The second component is the measure of mean luminance between the two signals whose dynamic range is (0, 1). The third component is a measure of how close the contrasts of the two signals are. Its dynamic range is also (0, 1). Thus, the quality index takes into account three factors namely, loss of correlation, luminance distortion and contrast distortion between two signals.

### 4.4.3.2 Proposed method

Similar to the previous methods, each cropped image is split into $n_p$ number of periodic blocks and quality indices of each periodic block with respect to itself and all other periodic blocks are calculated to get a similarity matrix (similar to correlation matrix) of size $n_p \times n_p$ as given below:

$$
Q = \begin{bmatrix}
q_{1,1} & q_{1,2} & \cdots & q_{1,n_p-1} & q_{1,n_p} \\
q_{2,1} & q_{2,2} & \cdots & q_{2,n_p-1} & q_{2,n_p} \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
q_{n_p-1,1} & q_{n_p-1,2} & \cdots & q_{n_p-1,n_p-1} & q_{n_p-1,n_p} \\
q_{n_p,1} & q_{n_p,2} & \cdots & q_{n_p,n_p-1} & q_{n_p,n_p}
\end{bmatrix}
$$

(4.37)

This similarity matrix is here referred to as quality index matrix. Since the quality index of a periodic block with itself is one and the quality index between $i^{th}$ periodic block and $j^{th}$ periodic block is same as the quality index between $j^{th}$ periodic block and $i^{th}$ periodic block, the similarity matrix becomes a diagonally symmetric matrix with diagonal elements being one as below:

$$
Q = \begin{bmatrix}
1 & & & & \\
q_{2,1} & 1 & & & \\
\vdots & \vdots & \ddots & \vdots & \\
q_{n_p-1,1} & q_{n_p-1,2} & \cdots & 1 & \\
q_{n_p,1} & q_{n_p,2} & \cdots & q_{n_p,n_p-1} & 1
\end{bmatrix}
$$

(4.38)

It may be noted that since the matrix is symmetric about the diagonal, the upper diagonal elements are not filled for the sake of simplicity. This similarity matrix does not yield directly any useful measure to discriminate between defective and defect-free periodic blocks. Hence, in order to extract useful measure for creating a feature space for cluster analysis and thereby to identify defective and defect-free clusters, the concept of Orthogonal Factor Model is utilized. According to the orthogonal factor
model, an observable random vector $X$ with $p$ components and mean vector $\mu$ can be expressed as a linearly dependent function of a few random variables $F_1, F_2, \ldots, F_m$, called common factors, and $p$ additional sources of variation $\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_p$ called errors or specific factors and can be given as (Johnson and Wichern, 2009)

$$
\begin{align*}
X_1 - \mu_1 &= l_{11}F_1 + l_{12}F_2 + \ldots + l_{1m}F_m + \varepsilon_1 \\
X_2 - \mu_2 &= l_{21}F_1 + l_{22}F_2 + \ldots + l_{2m}F_m + \varepsilon_2 \\
&\vdots \\
X_p - \mu_p &= l_{p1}F_1 + l_{p2}F_2 + \ldots + l_{pm}F_m + \varepsilon_p \\
\end{align*}
$$

(4.39)

where the coefficient $l_{ij}$ is called the loading of $i^{th}$ variable on $j^{th}$ factor. All these coefficients form the loading matrix $L$ of size $p \times m$. In matrix notation, equation (4.39) can be written as

$$
X - \mu = LF + \varepsilon
$$

(4.40)

where

$$
X = \begin{pmatrix}
X_1 \\
X_2 \\
\vdots \\
X_p
\end{pmatrix}, \mu = \begin{pmatrix}
\mu_1 \\
\mu_2 \\
\vdots \\
\mu_p
\end{pmatrix}, L = \begin{pmatrix}
\begin{pmatrix}
l_{11} & l_{12} & \cdots & l_{1m}
\end{pmatrix} \\
\begin{pmatrix}
l_{21} & l_{22} & \cdots & l_{2m}
\end{pmatrix} \\
\vdots \\
\begin{pmatrix}
l_{p1} & l_{p2} & \cdots & l_{pm}
\end{pmatrix}
\end{pmatrix}, F = \begin{pmatrix}
F_1 \\
F_2 \\
\vdots \\
F_p
\end{pmatrix}, \text{ and } \varepsilon = \begin{pmatrix}
\varepsilon_1 \\
\varepsilon_2 \\
\vdots \\
\varepsilon_p
\end{pmatrix}
$$

In terms of correlation matrix of $X$, equation (4.40) can be expressed as

$$
\rho = \text{Cor} (X) = LL^T + \Psi
$$

(4.41)

where $\rho$ is the correlation matrix of $X$, $L^T$ is the transpose of factor loading matrix of size $m \times p$, and $\Psi$ is the diagonal matrix containing specific variances as the diagonal elements. The portion of correlation of $i^{th}$ variable contributed by the $m$ common factors is called the $i^{th}$ communality and that due to specific factor is called uniqueness or specific variance. Representing the $i^{th}$ communality by $h_i^2$, equation (4.41) can be written as

$$
\rho_{ii} = h_i^2 + \psi_i, \text{ } i = 1, 2, \ldots, p
$$

(4.42)

where $h_i^2 = l_{i1}^2 + l_{i2}^2 + \ldots + l_{im}^2$. The $i^{th}$ communality is the sum of squares of the loadings of the $i^{th}$ variable on the $m$ common factors. If the off-diagonal elements in the correlation matrix $\rho$ are zero, the variables are not correlated and the factor analysis will not be useful. Under such circumstances, the specific factors are very much useful. In fact, the prime motive of the factor analysis is to estimate few significant common factors. Solving equation (4.41) involves estimation of the loading matrix $L$ and the specific variance
matrix \( \Psi \) from the correlation matrix \( \rho \) using techniques such as Principal Component Analysis (PCA) (Johnson and Wichern, 2009).

According to the method of PCA, the correlation matrix \( \rho \) can be written in terms of eigenvalue-eigenvector pairs \((\lambda_i, e_i)\) through eigen decomposition. Eigen decomposition or spectral decomposition is the factorization of a square matrix into a canonical form, where the square matrix is represented in terms of its eigenvalues and eigenvectors (Johnson and Wichern, 2009). Now, based on eigen decomposition, the symmetric matrix \( \rho \) can be factorized as \( \rho = EAE^T \), where, \( E \) is the orthogonal square matrix of size \( p \times p \) whose \( i^{th} \) column is the eigenvector \( e_i \) of \( E \) and \( A \) is the diagonal matrix whose diagonal elements are the corresponding eigenvalues, i.e., \( \Lambda_{ii} = \lambda_i \), such that \( \lambda_1 \geq \lambda_2 \geq \lambda_3 \geq \cdots \lambda_p \geq 0 \). In terms of components, \( \rho \) can be expressed as

\[
\rho = \lambda_1 e_1 e_1^T + \lambda_2 e_2 e_2^T + \cdots + \lambda_p e_p e_p^T
\]

(4.43)

In vectorial form, \( \rho \) can be expressed as

\[
\rho = \begin{bmatrix} \sqrt{\lambda_1} e_1 \\
\sqrt{\lambda_2} e_2 \\
\vdots \\
\sqrt{\lambda_p} e_p \end{bmatrix}
\]

(4.44)

If a factor model has as many factors as the variables \((m = p)\), then \( \Psi_i = 0 \) for all \( i \) and \( \rho = LL^T \). This does not allow any variation in the specific factor and hence the model is not useful. However, models that explain the correlation structure in terms of few common factors can be preferred for extraction of useful feature (specific variance) in certain applications. When \( m \) eigenvalues are enough for approximating the correlation matrix, the approximate representation of equation (4.44) with \( m \) factors can be given as

\[
\rho \approx \begin{bmatrix} \sqrt{\lambda_1} e_1 \\
\sqrt{\lambda_2} e_2 \\
\vdots \\
\sqrt{\lambda_m} e_m \end{bmatrix}
\]

(4.45)

Allowing for specific factors, for a \( m \)-factor model with \( m < p \), the approximation becomes
\[
\rho = \begin{bmatrix}
\sqrt{\lambda_1} e_1 & \sqrt{\lambda_2} e_2 & \cdots & \sqrt{\lambda_m} e_m
\end{bmatrix} +
\begin{bmatrix}
\psi_1 & 0 & \cdots & 0 \\
0 & \psi_1 & \cdots & 0 \\
\vdots & \vdots & \ddots & \vdots \\
0 & 0 & 0 & \psi_p
\end{bmatrix}
\] (4.46)

Since the quality index matrix is very similar to the correlation matrix in all its characteristics, \( \rho \) can be replaced with the quality index matrix \( Q \) in equation (4.46) and the specific variances estimated using \( m \) factor model can be used as a feature space in clustering algorithm to form two groups, namely, defective and defect-free clusters. The entire procedure for defect detection based on universal quality index is shown in the form of flow chart in Fig. 4.117.

Fig. 4.117: Defect detection scheme based on universal quality index.

4.4.3.3 Illustration of the proposed method

In order to illustrate the proposed method of defect detection, let us consider the same defective image (p4m image with thick bar defect – t16) as shown in Fig. 4.15. Quality indices are calculated for each block with respect to itself and all other periodic blocks and quality index matrix (similar to similarity matrix) is obtained for each cropped image. The quality index matrices thus obtained are shown in Fig. 4.118 in gray-scale form by scaling the matrix elements linearly in the range 0-255.
Fig. 4.118: Quality index matrix derived from the quality indices for the cropped image obtained from (a) top-left (b) bottom-left (c) top-right and (d) bottom-right corners of the test image shown in gray-scale.

It may be noted from Fig. 4.118 that the diagonal elements with gray value 255 in the symmetric quality index matrix indicate that the periodic blocks are of highest correlation with themselves. The gray scale representation clearly indicates that locations of dark pixels correspond to the defective periodic blocks having very high dissimilarity with respect to other periodic blocks. The quality index matrix from each cropped image is subjected to orthogonal factor analysis based on eigen decomposition using two-factor model to find the specific variances. The dissimilarity matrices calculated from the specific variance using Euclidean norm for all four cropped images are shown in gray scale in Fig. 4.119. The dendrograms resulting from Ward’s hierarchical clustering using the dissimilarity matrices are shown in Fig. 4.120 along with the defective periodic blocks. Boundaries of the defective periodic blocks thus identified from each cropped image are highlighted using white pixels and shown in Fig. 4.121. In the absence of false positives, we can employ the concept of defect-fusion as explained in other methods. The result of defect fusion for the test image used for algorithm demonstration is shown in Fig. A.5 in Appendix-I.
Fig 4.19 : Dissimilarity matrix derived from the specific variances extracted based on orthogonal factor model of UQI for the cropped image obtained from (a) top-left (b) bottom-left (c) top-right and (d) bottom-right corners of the test image shown in gray-scale.

Fig 4.120 : Dendrogram resulting from cluster analysis of specific variances obtained from the quality index matrix for the image cropped from (a) top-left (b) bottom-left (c) top-right and (d) bottom-right corners. It may be noted that since the cropped images have more number of periodic blocks, the identities of the periodic blocks in the abscissa are not shown in order to avoid crowd and to have better clarity.
Fig. 4.121: Defective blocks identified from the image cropped from (a) top-left (b) bottom-left (c) top-right and (d) bottom-right corners of the input image based on universal quality index. Boundaries of the defective periodic blocks are highlighted with white pixels.

4.4.3.4 Experimental analysis

Defective images from all three major wallpaper groups are tested using the method of UQI and the performance measures are given in Table-4.6.

Table – 4.6: Performance parameters for UQI based method of defect detection

<table>
<thead>
<tr>
<th>Wallpaper group</th>
<th>Defect</th>
<th>Precision (%)</th>
<th>Recall (%)</th>
<th>Accuracy (%)</th>
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<td>pmm Broken end</td>
<td>90.70</td>
<td>88.71</td>
<td>92.22</td>
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</tr>
<tr>
<td>pmm Hole</td>
<td>8.53</td>
<td>21.13</td>
<td>56.43</td>
<td></td>
</tr>
<tr>
<td>pmm Thin bar</td>
<td>69.57</td>
<td>97.51</td>
<td>88.97</td>
<td></td>
</tr>
<tr>
<td>pmm Thick bar</td>
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<td>86.08</td>
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</tr>
<tr>
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<td>80.83</td>
<td></td>
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<td>84.27</td>
<td></td>
</tr>
<tr>
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<td>79.74</td>
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</table>
4.4.3.5 Conclusion

The following can be concluded from the proposed method of defect detection based on universal quality index:

(i) The method is based on simple first order statistics.

(ii) Eigen-vale decomposition technique is effectively used for extraction of specific variance from the universal quality index matrix through orthogonal factor model.

(iii) Specific variance extracted from the universal quality index matrix is utilized as feature space for the defect detection method.

(iv) In the absence of false positive, fusion of defects identified from four cropped images generated from the input image helps in getting an overview of the total defects.

4.5 Overall comparative analysis

Given several defect detection algorithms, it is necessary to compare them in terms of performance and computational time. In many inspection systems that apply defect detection algorithms for quality assurance, the computational time is critical while implementing the algorithm in real-time application. Hence, analysis on computational time of an algorithm is as important as analysis on performance of the algorithm. This section focuses on comparative analysis of all defect detection methods in terms of performance and computational time.

4.5.1 Comparative analysis on performance of all defect detection methods

Summary of performance parameters for each defect detection method for the defective test images of each wallpaper group is shown in Table-4.7 where WPG represents the wallpaper group; and the alphabets P, R, and A represent the performance measures – precision, recall and accuracy, respectively. These performance parameters are averaged for all test images and shown in Table-4.8 for each defect detection method.
Table – 4.7: Summary of performance parameters from each method for the defective test images of each wallpaper group

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<th>WPG</th>
<th>Defect</th>
<th>Gabor wavelet</th>
<th>HVP contrast</th>
<th>Chi square</th>
<th>JS divergence</th>
<th>UQI</th>
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Table – 4.8: Summary of performance parameters from each method for all test images

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<th>Recall (%)</th>
<th>Accuracy (%)</th>
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<td>Method based on Gabor wavelet</td>
<td>64.52</td>
<td>75.59</td>
<td>84.4</td>
</tr>
<tr>
<td>Method based on HVP contrasts</td>
<td>61.57</td>
<td>75.71</td>
<td>88.46</td>
</tr>
<tr>
<td>Method based on chi-square distance</td>
<td>58.79</td>
<td>76.66</td>
<td>84.63</td>
</tr>
<tr>
<td>Method based on JS divergence</td>
<td>52.69</td>
<td>68.53</td>
<td>82.76</td>
</tr>
<tr>
<td>Method based on UQI</td>
<td>53.34</td>
<td>81.19</td>
<td>85.76</td>
</tr>
</tbody>
</table>

The accuracies of the HVP based methods for pmm, p2 and p4m defective images are shown graphically in Figs. 4.122, 4.123 and 4.124, respectively. The precision rate is slightly better in Gabor wavelet based method than that in HVP contrast based method due to filtering action in the Gabor wavelet based method. There is not much change in recall rate between the two HVP based methods. The accuracies of the non-HVP based methods for pmm, p2 and p4m defective images are shown in Figs. 4.125, 4.126 and 4.127, respectively. Average accuracy does not vary much among these three methods. Precision rate for these three non-HVP methods is slightly less than that of HVP based methods. Relatively less recall rates in all methods indicate that there are few false negatives identified by the proposed methods. On an average, overall accuracy for HVP contrast based method is slightly better than that of Gabor wavelet based method and other three non-HVP based methods. This reveals that HVP based contrast can replace human vision based defect detection. This method can be further extended and can be thought of implementation in automated inspection scheme.
Fig. 4.122 : Accuracy of HVP based methods for pmm group.

Fig. 4.123 : Accuracy of HVP based methods for p2 group.
Defect in p4m images

Fig. 4.124: Accuracy of HVP based methods for p4m group.

Defect in pmm images

Fig. 4.125: Accuracy of non-HVP based methods for pmm group.
Fig. 4.126 : Accuracy of non-HVP based methods for p2 group.

Fig. 4.127 : Accuracy of non-HVP based methods for p4m group.
The accuracies of the proposed methods are compared with other supervised methods available in literature and given in Table-4.9. In general, the accuracy of a defect detection algorithm depends on so many factors such as the lighting condition for the imaging system, noises, distortions, preprocessing, post-processing, type of defects, category of the test image wallpaper group, and the number of test samples. In other supervised methods available in literature that involve training stage with defect-free samples for thresholds or decision boundaries, the overall accuracy or success rate varies from 78.3% to 99.4%. These methods either assume that the periodicity is known from defect-free samples or locate the lattices manually for defect detection and are based on limited number of test images or periodic samples. Our methods are based on maximum number of test images and periodic samples resulting in more realistic conditions (based on 324 test images for Gabor wavelet based method, and 274 test images for other methods; and 32340 periodic samples for Gabor wavelet based method, and 26520 periodic samples for other methods). Though all our methods do not involve any preprocessing or post-processing or any training stage, our methods yield a very good success rate between 82.8% and 88.5%. For a defect detection method without preprocessing, post-processing or any training stage, the success rate between 82.8% and 88.5% itself is quite high.
Table – 4.9 : Comparison of success rates for all defect detection methods

<table>
<thead>
<tr>
<th>Method</th>
<th>Authors</th>
<th>Test images / wallpaper groups</th>
<th>Total no. of test images/ lattices/ periodic blocks</th>
<th>Accuracy or success rate (%)</th>
<th>Remarks</th>
</tr>
</thead>
<tbody>
<tr>
<td>GIS method</td>
<td>Ngan et al., 2005</td>
<td>pmm</td>
<td>30 images / 30 images</td>
<td>100 / 56.7 / 78.3</td>
<td>- Involves training stage</td>
</tr>
<tr>
<td>DT</td>
<td>Ngan et al., 2005</td>
<td>pmm</td>
<td>30 images / 30 images</td>
<td>86.8 / 90.0 / 88.3</td>
<td>- Involves training stage</td>
</tr>
<tr>
<td>WGIS method</td>
<td>Ngan et al., 2005</td>
<td>pmm</td>
<td>30 images / 30 images</td>
<td>93.3 / 100 / 96.7</td>
<td>- Involves training stage</td>
</tr>
<tr>
<td>BB method</td>
<td>Ngan and Pang, 2006</td>
<td>pmm, p2 &amp; p4m</td>
<td>165 images / 175 images</td>
<td>100 / 97.1 / 98.6</td>
<td>- Involves training stage</td>
</tr>
<tr>
<td>RB method</td>
<td>Ngan and Pang, 2010</td>
<td>pmm, p2 &amp; p4m</td>
<td>85 images / 81 images</td>
<td>100 / 98.8 / 99.4</td>
<td>- Involves training stage</td>
</tr>
<tr>
<td>LBP method</td>
<td>Tajeripour et al., 2007</td>
<td>pmm, p2 &amp; p4m</td>
<td>3 images / 16 images</td>
<td>--- / 95.0 / 95.0</td>
<td>- Involves training stage</td>
</tr>
<tr>
<td>EV-MMDR</td>
<td>Ngan et al. (2008; 2010)</td>
<td>pmm, p2 &amp; p4m</td>
<td>120 lattices / 233 lattices</td>
<td>--- / 93.3 / 93.3</td>
<td>- Involves training stage</td>
</tr>
<tr>
<td>EV-EDR</td>
<td>Ngan et al. (2010)</td>
<td>pmm, p2 &amp; p4m</td>
<td>120 lattices / 233 lattices</td>
<td>--- / 95.8 / 95.8</td>
<td>- Involves training stage</td>
</tr>
<tr>
<td>Proposed method</td>
<td>Asha et al., 2012</td>
<td>pmm, p2 and p4m</td>
<td>--- / 324 images (32340 periodic blocks)</td>
<td>--- / 84.4 / 84.4</td>
<td>No training stage</td>
</tr>
<tr>
<td>Proposed method</td>
<td>Asha et al., 2012</td>
<td>pmm, p2 and p4m</td>
<td>--- / 274 images (26520 periodic blocks)</td>
<td>--- / 88.5 / 88.5</td>
<td>No training stage</td>
</tr>
<tr>
<td>Proposed method</td>
<td>Asha et al., 2012</td>
<td>pmm, p2 and p4m</td>
<td>--- / 274 images (26520 periodic blocks)</td>
<td>--- / 84.6 / 84.6</td>
<td>No training stage</td>
</tr>
<tr>
<td>Proposed method</td>
<td>Asha et al., 2012</td>
<td>pmm, p2 and p4m</td>
<td>--- / 274 images (26520 periodic blocks)</td>
<td>--- / 82.8 / 82.8</td>
<td>No training stage</td>
</tr>
<tr>
<td>Proposed method</td>
<td>Asha et al., 2012</td>
<td>pmm, p2 and p4m</td>
<td>--- / 274 images (26520 periodic blocks)</td>
<td>--- / 85.8 / 85.8</td>
<td>No training stage</td>
</tr>
</tbody>
</table>
4.5.2 Comparative analysis on computational time for all defect detection methods

The computational time for the test images in each wallpaper group is shown in Fig. 4.128 through Fig. 4.132 for the defect detection method based on Gabor wavelet, HVP contrasts, chi-square distance, Jensen-Shannon divergence and UQI. The average computational time for each method is shown in Table-4.10. Based on the analysis of computational time, we can conclude the following: Keeping the image size fixed, when the number of periodic blocks increases, the computational time also increases. However, the increase in magnitude varies from one method to another. The average computational time for the defect detection method based on Gabor wavelet is the least and the computational time for Jensen-Shannon divergence based method is the highest. The second least computational time can be seen in HVP contrast based method. Though performance of Jensen-Shannon divergence based method is comparable with chi-square distance based method, the computational time is higher for Jensen-Shannon divergence based method. Since other methods in literature consider images with complete number of lattices, the average computational time for an image with complete number of periodic blocks is shown in Fig. 4.133 for the proposed methods along with other methods in literature. All methods proposed by us have less computational time than the methods available in literature such as Bollinger Bands method, Regular Bands method, energy-variance method with min-max decision regions, energy-variance method with ellipsoidal decision regions as seen in Fig. 4.133.
Fig. 4.12: Computational time for defect detection method based on Gabor wavelets for (a) pmm, (b) p2 and (c) p4m defective images.
Fig. 4.129: Computational time for defect detection method based on HVP contrasts for (a) pmm, (b) p2 and (c) p4m defective images.
Fig. 4.130: Computational time for defect detection method based on chi-square distance for (a) pmm, (b) p2 and (c) p4m defective images.
Fig. 4.131: Computational time for defect detection method based on Jensen-Shannon divergence for (a) pmm, (b) p2 and (c) p4m defective images.
Fig. 4.132 : Computational time for defect detection method based on universal quality index for (a) pmm, (b) p2 and (c) p4m defective images.
Table-4.10: Computational time for the proposed defect detection methods

<table>
<thead>
<tr>
<th>Method</th>
<th>Wallpaper group</th>
<th>Number of periodic blocks in a defective image</th>
<th>Computational time, s</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Averaged for all defective images</td>
</tr>
<tr>
<td>Gabor wavelet based method</td>
<td>PMM</td>
<td>54</td>
<td>0.170</td>
</tr>
<tr>
<td></td>
<td>P2</td>
<td>165</td>
<td>0.197</td>
</tr>
<tr>
<td></td>
<td>P4M</td>
<td>90</td>
<td>0.192</td>
</tr>
<tr>
<td>HVP contrast based method</td>
<td>PMM</td>
<td>63</td>
<td>1.048</td>
</tr>
<tr>
<td></td>
<td>P2</td>
<td>192</td>
<td>1.155</td>
</tr>
<tr>
<td></td>
<td>P4M</td>
<td>90</td>
<td>1.124</td>
</tr>
<tr>
<td>Chi-square distance based method</td>
<td>PMM</td>
<td>63</td>
<td>0.511</td>
</tr>
<tr>
<td></td>
<td>P2</td>
<td>192</td>
<td>3.780</td>
</tr>
<tr>
<td></td>
<td>P4M</td>
<td>90</td>
<td>0.947</td>
</tr>
<tr>
<td>Jensen-Shannon divergence based method</td>
<td>PMM</td>
<td>63</td>
<td>1.857</td>
</tr>
<tr>
<td></td>
<td>P2</td>
<td>192</td>
<td>14.477</td>
</tr>
<tr>
<td></td>
<td>P4M</td>
<td>90</td>
<td>3.550</td>
</tr>
<tr>
<td>Universal quality index based method</td>
<td>PMM</td>
<td>63</td>
<td>0.485</td>
</tr>
<tr>
<td></td>
<td>P2</td>
<td>192</td>
<td>2.610</td>
</tr>
<tr>
<td></td>
<td>P4M</td>
<td>90</td>
<td>0.786</td>
</tr>
</tbody>
</table>
Fig. 4.133: Comparison of computational time for the proposed defect detection methods with literature. BB, RB, EV-MMDR, EV-EDR, GABOR, HVP-CONT, CSD, JSD and UQI represent Bollinger Bands method, Regular Bands method, energy-variance method with min-max decision regions, energy-variance method with ellipsoidal decision regions, Gabor wavelet based method, HVP contrast based method, chi-square distance based method, Jensen-Shannon divergence based method, and universal quality index based method, respectively.

4.7 Conclusion

The following can be concluded from the defect detection methods proposed by us:

(i) The proposed defect detection methods do not involve any preprocessing or post-processing or any training stage for obtaining threshold or decision boundaries.

(ii) Periodicities are extracted from the defective test images unlike other methods which assume that the size of the periodic block is known. In order to arrive at appropriate row and column periodicities from defective images of each wallpaper group, frequency plots are made from the maxima extracted from the second derivative plots of overall DMFs. Row or column periodicity with high frequency of occurrence is considered for arriving at the average size of the test images for each wallpaper group. This approach of selecting the periodicity with high frequency of occurrence eliminates the low frequency data resembling noises.
Most of the texture analysis methods for periodically patterned textures are based on the assumption that the images have complete number of periodic blocks. In practice, an image under inspection can have fractional periodic blocks also. Hence, a method of analyzing such images is proposed based on cropping of the input image into four images, each containing complete number of periodic blocks without worrying about location of lattice points.

Concept of defect fusion from all cropped images is introduced. In the absence of false positive, fusion of defects identified from four cropped images generated from the input image helps in getting an overview of the total defects.

Our methods are tested on maximum number of test images and periodic samples by bringing in more realistic conditions (based on 324 test images for Gabor wavelet based method and 274 test images for other methods; and 32340 periodic samples for Gabor wavelet based method and 26520 periodic samples for other methods).

Though all our methods do not involve any preprocessing or post-processing or any training stage, our methods yield a very good success rate between 82.8% and 88.5%. For a defect detection method without preprocessing, post-processing or any training stage, the success rate between 82.8% and 88.5% itself is quite high.

The computational time of the proposed methods of defect detection is less than that of other methods in literature, namely, Bollinger Bands method, Regular Bands method, energy-variance method with min-max decision regions, energy-variance method with ellipsoidal decision regions.