5. DESIGN OF NON-MOTIF-BASED ALGORITHMS

Defect recognition from images is becoming increasingly significant in a variety of applications since quality control plays a prominent role in contemporary manufacturing of virtually every product. As mentioned in Chapter 1 (Introduction) and Chapter 2 (Review of Literature), it is understood that the techniques to identify faults in patterned fabric can be either non-motif based techniques or motif-based techniques. The second phase of the proposed patterned fabric defect detection system focuses on designing and developing non-motif-based methods. In particular, two imaging technologies, namely, image data fusion and wavelet transformation, are being analyzed and enhanced for this purpose. This chapter presents the required introduction to these technologies, followed by detailed working process of the proposed algorithms that use the two selected imaging technologies.

5.1. IMAGE DATA FUSION-BASED SYSTEM

The proposed system based on data fusion can be used when multiple inspections provide complementary information about the fabric and combining the data may facilitate the analysis or classification process. Data fusion techniques provide a framework to fuse and integrate information from multiple sources.

The concept of data fusion is relatively simple but its implementation remains challenging. Fusion refers to the acquisition, processing and synergistic combination of information gathered by various sources to provide a better understanding of the phenomenon under consideration. In this study, this phenomenon is the patterned fabric sample.

According to Wald (1999), data fusion is a formal framework in which images are expressed by tools for the alliance of data originating from different sources. It aims at obtaining information of greater quality. Fusion of image data is an integrated process that combines image data (features) obtained from various sources acquired at varying time or using diversified methods. The fusion is performed either based on the analysis of a knowledge based or using specified decision rules. The image obtained after image fusion contains more precise description and can provide more information that can be used to increase the accuracy of patterned fabric defect decision.

During fusion, this technology extracts various kinds of data from the image and uses decision rules for deciding the method of combining. The analysis is based on the assumption that useful information in each image in a sequence (or in different results from the same image by different processing methods) can be correlated, while noise in the images will not correlate. Therefore, precise image information can be obtained without noise by comparing and analyzing various data sets. Image data fusion can be performed in two manners.

- Merging data from multiple sources to optimize data or create "value added" data

- Using multiple sources of data for a statistical estimate where the data "interacts" to enhance predictive power.

This study focuses on the second type and is used to detect defects in a 2-dimensional patterned fabric image. The main goal here is to produce a fused result that provides the most detailed and reliable information possible and produces a more efficient representation of the data. The proposed image data based fusion system for patterned fabric defect detection consists of the steps listed below and is illustrated in Figure 5.1.

Step 1 : Enhance input image using preprocessing algorithm

Step 2 : Image Data Extraction

Step 3 : Image Data Fusion

Step 4 : Defect Detection

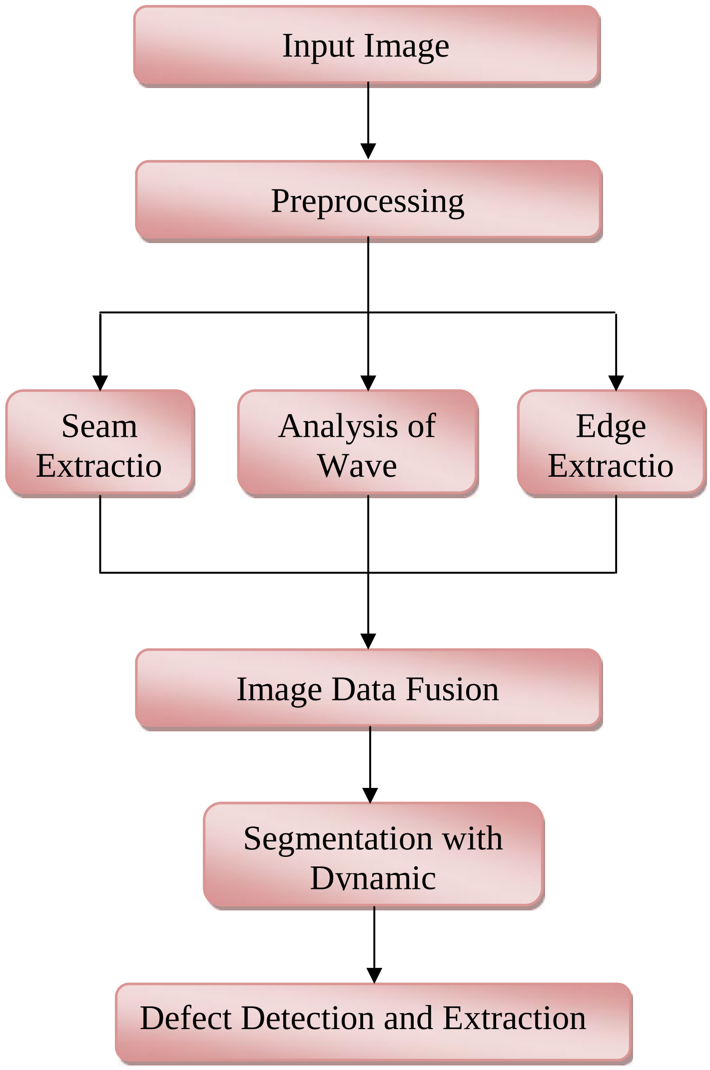


Figure 5.1 : Image Data Fusion-Based System

The input patterned fabric image is first enhanced by removing unwanted noisy pixels. The techniques used for this purpose are described in the previous chapter (Chapter 4).

5.1.1. Image Data Extraction

The proposed system uses three types of image edge data during defect detection. They are edge, seam line and wave profiles. These features are then fused together by using a dynamic thresholding method and defects are identified. This section presents the methods used to extract three image data.

A) Sobel Operator based Edge Detection

Sobel Operator was discovered by Irwin Sobel. It uses a 3x3 convolution mask which is the x and y direction on the image. It is discovered at first derivative level. In the fusion based defect detection system, the Sobel method is used for edge extraction and is preferred due to higher processing speed, better continuity, and ability to identify thinner lines. The sobel edge detector is described using Equations (5.1) and (5.2).

$$S(m,n) = \sqrt{S_x^2 + S_y^2} \quad (5.1)$$

$$\theta = \arctan(S_y / S_x) \quad (5.2)$$

where $S_x = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ +1 & +2 & +1 \end{bmatrix} * I$ and $S_y = \begin{bmatrix} -1 & 0 & +1 \\ -2 & 0 & +2 \\ -1 & 0 & +1 \end{bmatrix} * I$. Both these denote the horizontal and vertical pixel masks for sobel operator used during edge detection. S(m, n) and θ are the amplitude and the angle of the Sobel edge at location (m, n).

B) Wave Profiles

The wave profile analysis analyzes information in the wave profile of the intensity curve for every line of pixels. Local distortions of the wave profile indicate information of fabric defects. The common characteristics of the wave shape include the gradient, local maximum, mean, and variance of the curve.

C) Seam Line

A seam line is the line along which pieces of fabric (lattices) are joined, especially through stitching. It is the ridge or line joining two edges. Some examples of seam lines are shown in Figure 5.2.

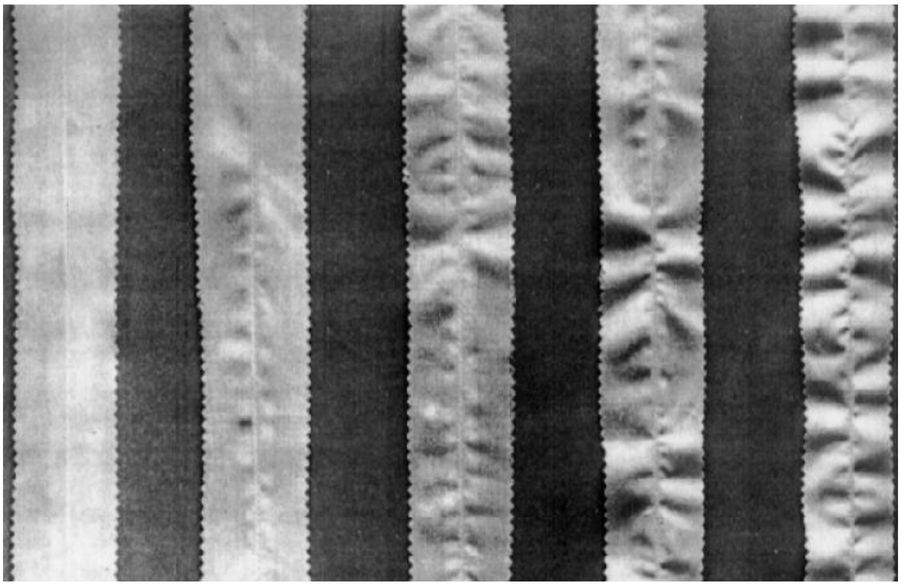


Figure 5.2 : Seam Lines in Fabric Images

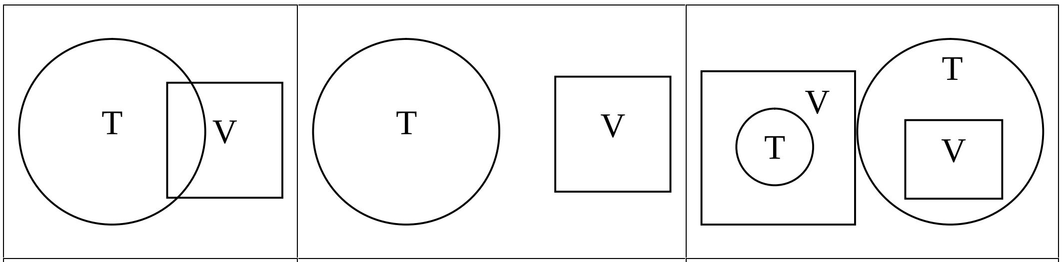
In the present study, seam lines are detected using Hough Transformation procedure (Duda and Hart, 1972) using the method suggested by Mak and Li (2008). Hough transformation has been recognized as one of the most popular methods for the detection of line segments having good stability and robustness when working on images where noise is present. The idea of Hough transform is to describe a certain line shape (straight lines, circles, ellipses, etc.) globally in a parameter space, that is, the Hough transform domain. In the Hough space, straight lines are specified using Equation (5.3).

$$\rho = x \cos \theta + y \sin \theta \qquad (5.3)$$

where ρ is the perpendicular distance from the origin and θ is the angle with the normal. Collinear points (x_i, y_i), with i = 1, 2. …, N, are transformed into N sinusoidal curves $\rho = x_i \cos \theta + y_i \sin \theta$ in the Hough plane, which intersect in the point (ρ, θ). The value of a function in Hough space gives the point density along a line in the input space. A straight line is defined in the input space if there is a peak point in Hough space and it is the cumulative value of all the sinusoids. In this work, the point with the maximum density in the Hough space is considered as the seam line.

5.1.2. Image Data Fusion

The image data fusion method used is a feature-level fusion technique. The feature level fusion algorithm operates on the features based on their relationships shown graphically in Figure 5.3, in which circle T and V are features extracted from the image.



(a) Intersection	(b) Disjoint	(c) Inclusion

Figure 5.3 : Feature Relationships

The above feature relationships can be mathematically represented as in Equation 5.4.

$$\begin{cases} F = T \;\text{Ć}\; V & \textbf{Intersection} \\ F = T \;\text{õ}\; V & \textbf{Disjoint} \\ F = T \;\text{ą}\; V & \textbf{Inclusion} \end{cases} \qquad (5.4)$$

In Intersection condition, both detected features contain incomplete information of the same object. Thus, an OR operation is applied to keep complementary information and remove redundant information. In Disjoint condition, each detected feature contains the information for different object. Thus, an OR operation is applied to keep both of them. In Inclusion condition, both detected features contain the information of the same object. However, one feature includes the other one. In the study, the union condition is applied to obtain more concise information of the image.

5.1.3. Defect Detection

Most of the faults in fabrics can be viewed as sudden changes in texture in the fabric images. In these situations, the intensity plays a vital role during defect detection. This method relies heavily on the richness of edge information, which is different in the edges extracted by the different approaches. The edge data obtained are fused using the technique described in the previous section.

The use of edge detection to determine the number of edge pixels in a specified region helps determine a characteristic of texture complexity. After edges have been found the direction of the edges can also be applied as a characteristic of texture and can be useful in determining patterns in the texture. These directions can be represented as an average or in a histogram.

Three types of edges, extracted from the input image, are analyzed for fabric fault defect detection. The methods used are Sobel operator, wave profiles and seam line extraction method (Section 5.1.1).

The use of image texture can be used as a description for regions into segments. There are two main types of segmentation based on image texture, region based and boundary based. In this study, the boundary based segmentation is performed using the edgeness obtained above. For this purpose a dynamic thresholding based segmentation algorithm is used.

Since defect areas are small whose intensities are not uniform, they cannot be extracted using a single threshold. This method uses a thresholding method to obtain a smoothened version of the original image. The next step then segments the original image with the smoothed image as the threshold surface. As a result, defects in the different intensity are evident since the intensities in defects are always higher than the intensities of their neighborhood. An example is shown in Figure 5.4, where points p1 and p2 are defects.

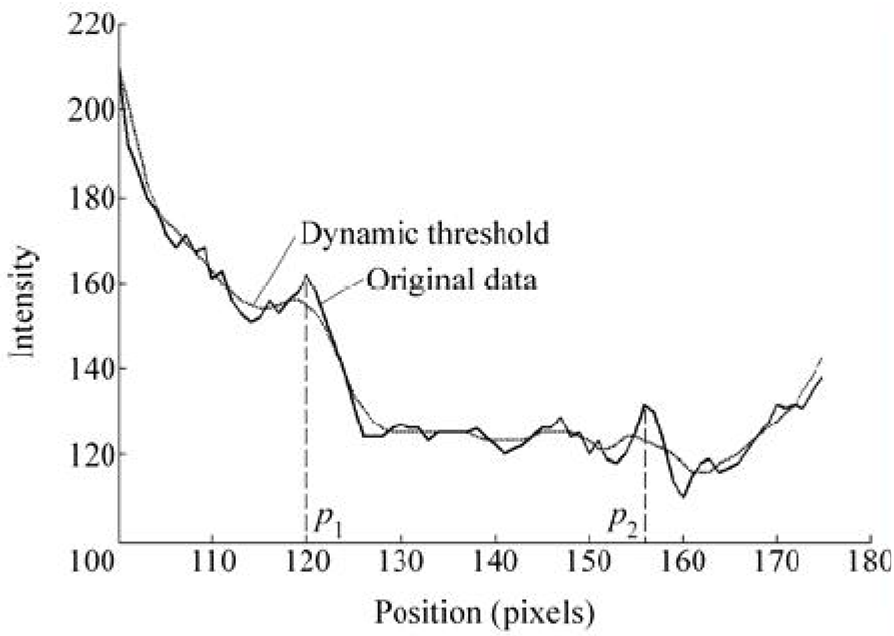


Figure 5.4 : Segmentation Example with Dynamic Thresholds

5.2. WAVELET-BASED ALGORITHM

The second part of Phase II is involved in the use of wavelet transformation with image processing techniques for defect detection in patterned fabrics. In this section, the existing wavelet-based algorithm along with the issues that needs to resolved are discussed.

The Golden Image Subtraction (GIS) method for fabric defect detection has been frequently used by several researchers for the past few decades. This method uses a golden image (image without defect) and thresholding method to detect defects in fabrics. Inspite of its success in detecting defects, the method also has some serious flaws when used with patterned fabrics.

(i) The GIS method is a 2-D approach and therefore has high complexity

(ii) With patterned fabric, as image complexity increases, the GIS method cannot detect right and bottom borders

(iii) Similarly when applied to fabrics having binary patterned texture (black and white texture), the GIS method completely fails. An example of such an image is shown in Figure 5.5, where the energies of GIS range between 0 and 1.

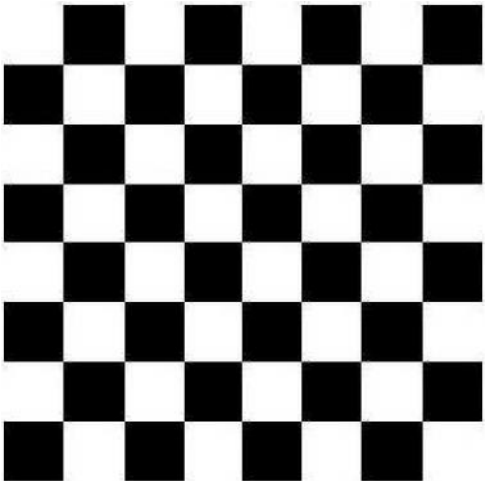


Figure 5.5 : Binary Patterned Fabric Image

Ngan *et al.* (2005) proposed a solution to these issues by proposing a Wavelet based GIS method using Direct thresholding was proposed. This model is referred as WGIS in this thesis. The WGIS model performed defect detection in four steps, namely, wavelet decomposition using Haar wavelet, applying GIS method, defect detection using thresholding method, and post processing for removal of noise in defective regions. This research study proposes methods that can be used to enhance the fault detection accuracy of the WGIS method. The enhancement operations are brought forward in two manners.

(i) The WGIS model uses Haar Wavelet Transformation, which is replaced by a more sophisticated wavelet variant. For this purpose, two methods, namely, Optimal Tree Wavelet Transformation, Wavelet Transformation with VQ and PCA and Gabor Wavelet Network are used and analyzed.

(ii) To reduce complexity, instead of using all wavelet coefficients, the study proposes the use of three optimal wavelet coefficient selection techniques, namely,

a. Vector Quantization and Principal Component
b. Independent Component Analysis

c. The above two selection methods are also combined to form multiple projection selection algorithms.

(iii) The algorithm proposes the use of neural network based segmentation of defective regions in the patterned fabric apart from using the golden image subtraction method using direct thresholding method

(iv) The algorithm uses median filtering and weiner filtering as post processing step to remove noise in recognized defect regions. In this research, the method proposed in Phase I (Chapter 4, Preprocessing Technique) is used for this purpose.

5.3. PROPOSED DEFECT DETECTION METHOD

The steps involved in the proposed fabric defect detection method are shown in Figure 5.6 and are explained in the following sub-sections.

5.3.1. Histogram Equalization

An image histogram is a graphical representation of the tonal distribution in a digital image. Histogram Equalization (HE), an approach based on histograms, is a global contrast enhancement technique which results in a histogram which has an approximate constant for all values. A histogram of an image is technically defined as follows.

Let I(N, G) be an input image, where N denotes that the image is of size N x N and G denotes the gray levels of the image and is in the range 0 .. L-1. In 8-bit images, L ranges from 0-256. A Histogram, H, of I is then defined as a discrete function that maps each G to the number of pixels in the image characterized by that gray level, that is, $H(G_{r_i}) = n_i$ where r is the r^{th} gray level of pixel i and 'n' is the number of pixels having values same as G_r.

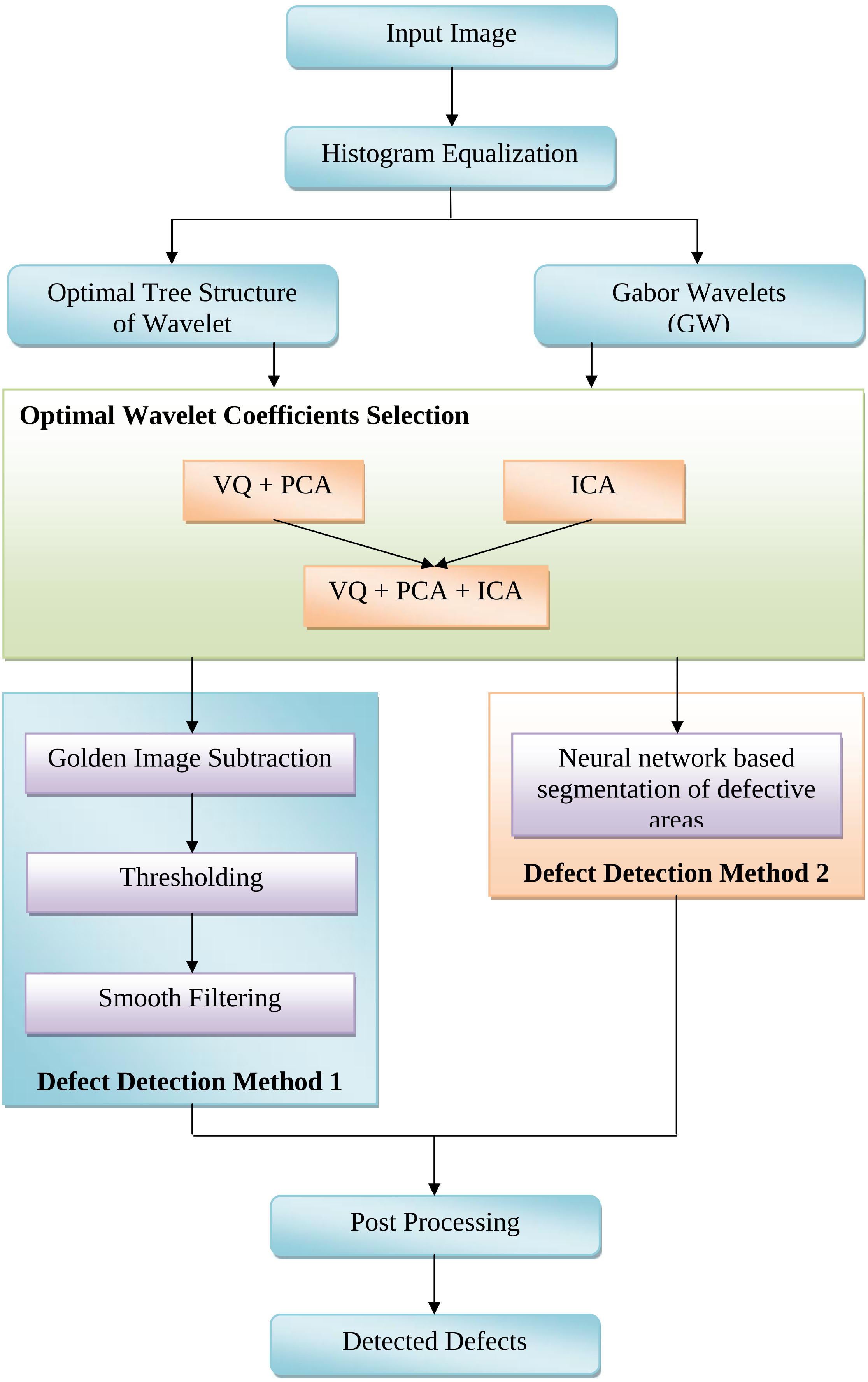
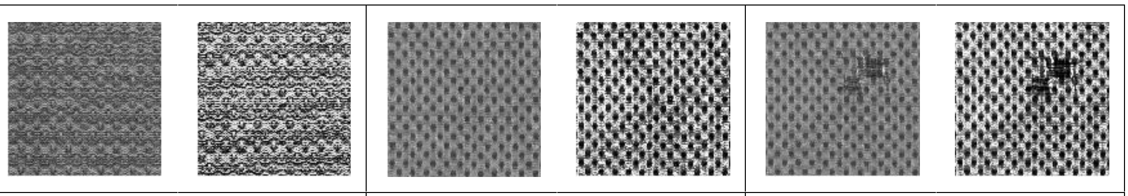


Figure 5.6 : Wavelet-Based Defect Detection Systems

HE attempts to create an enhanced version of the degraded image by uniformly distributing the intensity of the pixels over the entire intensity scale. The process also adjusts the contrast of the image by spreading the frequent intensity values again over the intensity scale. An example of defective fabric before and after histogram equalization is presented in Figure 5.7.



(a)	(b)	(c)

Figure 5.7 : Effect of Histogram Equalization

To equalize the brightness (lighting variation) in I, the image pixels are normalized to obtain a probability density function (pdf) and is represented using Equation (5.5).

$$p_r(G_{r_i}) = n_k/N^2 \qquad (5.5)$$

and the above equation satisfies the following :

(i) $p_r(G_{r_i})$ is between 0 and 1

(ii) Summation of $p_r(G_{r_i})$ is always equal to 1

For this reason, $p_r(G_{r_i})$ is often referred as the probability of occurrence of gray level G_{r_i}. The histogram equalization function is obtained using the cumulative distribution function (cdf) of G_{r_i} which is computed from pdf. The cdf S_r at rth intensity level in the image is calculated using Equation (5.6).

$$S_r = T(I_r) = \sum_{j=0}^{r} p_r(G_{r_i}) = \sum_{j=0}^{r} \frac{n_j}{n} \qquad (5.6)$$

where r ranges from 0 to L-1 and $T(I_{r-1})$ is equal to 1. As the histogram of equalized images have uniform distribution, the density function of the output image is also equally distributed over the entire image.

5.3.2. Wavelet Decomposition Techniques

As mentioned earlier, two types of wavelet decomposition techniques are studied for defect detection. The first method enhances Haar wavelet decomposition with optimal tree structure and the second method proposes the use of Gabor Wavelet Network (GWN). This section presents the concepts of wavelet decomposition, Haar wavelets, Optimal tree structure for wavelet decomposition and GWN.

A) Wavelets

The heart of the proposed defect detection algorithms is the wavelet transformation technique. The wavelet transform (WT) has been developed over 20 years and successfully applied in defect detection on plain (non-patterned) fabric. This work is on the use of the wavelet transform to develop an automated visual inspection method for defect detection on patterned fabric.

Wavelets are mathematical functions that can be used to divide a given signal into different frequency components. The components can then be studied individually with a resolution that matches its scale. A wavelet transform is the representation of a function by wavelets.

The wavelet transformation technique works by applying the transform to one row at a time, then transforming the columns. Let the sequence f_0, f_1, ..., f_n describe the values of grey scale components in a row of pixels. The aim is to separate rapid changes in the sequence from slower changes. To this end, a sequence of wavelet coefficients is created as below:

$$\begin{aligned} a_0 &= (f_0 + f_1)/2 \\ a_1 &= (f_0 - f_1)/2 \\ a_2 &= (f_2 + f_3)/2 \\ a_3 &= (f_2 - f_3)/2 \\ \vdots &= \vdots \end{aligned}$$

Wavelets have the added advantage that even coefficients record the average of two successive values. This is called as the low pass band since information about high frequency changes is lost. While the odd coefficients record the difference in two successive values and is called as the high pass band as high frequency information is passed on. The number of low pass coefficients is half the number of values in the original sequence (as is the number of high pass coefficients). The original f values can be recovered from the wavelets for reconstructing the image as given in Equation (5.7).

$$f_0 = a_0 + a_1 \qquad f_1 = a_0 - a_1 \qquad (5.7)$$

The wavelet coefficients are reordered by listing the low pass coefficients first followed by the high pass coefficients. The same operation is applied to transform the wavelet coefficients vertically. This result in a 2-dimensional grid of wavelet coefficients divided into four blocks by the low and high pass bands (Figure 5.8a). The LL region is obtained by averaging the values in a 2 x 2 block and so represents a lower resolution version of the image. In practice, the image is broken into tiles, usually of size 64 x 64. If the coefficients in the LL region are transmitted first, the image at a lower resolution can be reconstructed before all the coefficients had arrived. The same operation is performed on the lower resolution image in the LL region thereby obtaining images of lower and lower resolution (Fig. 5.8b). The wavelet coefficients are computed through a lifting process as below in Equation (5.8).

$$a_0 = (f_0 + f_1) / 2 \qquad a_1 = a_0 - f_1 \qquad (5.8)$$

The advantage is that the coefficients may be computed without using additional computer memory, that is, a_0 first replaces f_0 and then a_1 replaces f_1. Also, the lifting process enables faster computation of the coefficients.

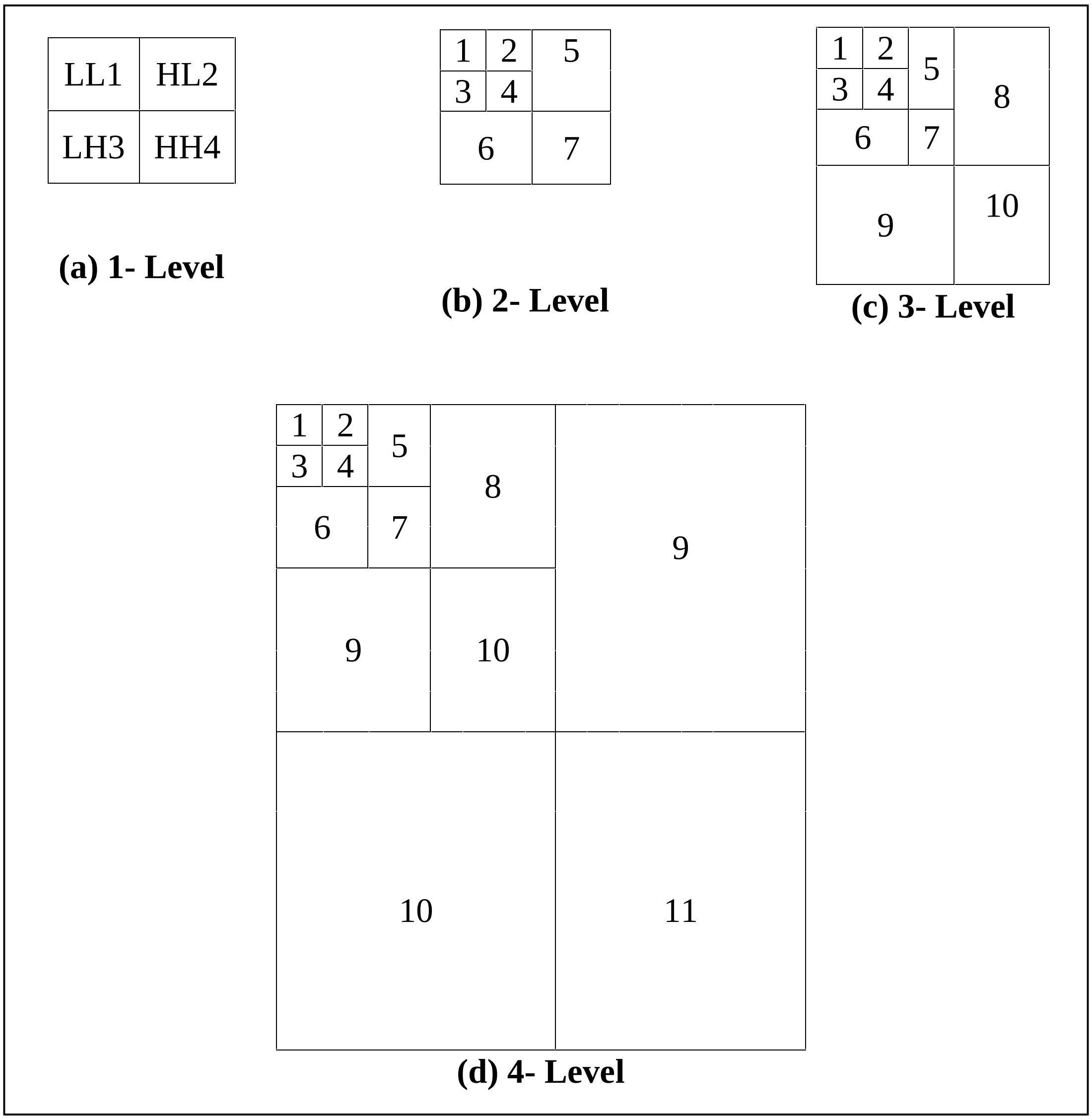


Figure 5.8: Image Decomposition

B) Haar wavelet

The first DWT was invented by the Hungarian mathematician Alfréd Haar in 1910 (http://en.wikipedia.org/wiki/Discrete_wavelet_transform). For an input represented by a list of 2^n numbers, the Haar wavelet transform may be considered to simply pair up input values, storing the difference and passing the sum. This process is repeated recursively, pairing up the sums to provide the next scale: finally resulting in 2^n-1 differences and one final sum.

In mathematics, the Haar wavelet is a sequence of rescaled "square-shaped" functions which together form a wavelet family or basis (Figure 5.9).

Wavelet analysis is similar to Fourier analysis in that it allows a target function over an interval to be represented in terms of an orthonormal function basis.

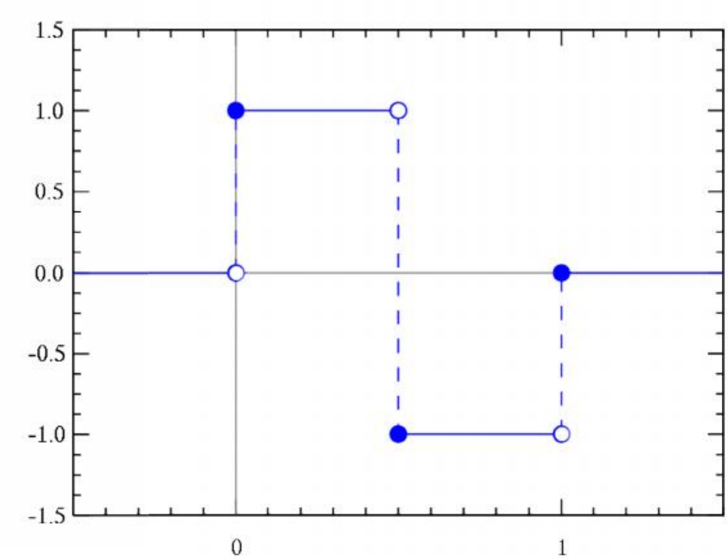


Figure 5.9 : Haar Wavelets

The Haar wavelet's mother wavelet function ψ(t) can be described as in Equation (5.9).

$$\Psi(t) = \begin{cases} 1 & 0 < t < 1/2 \\ -1 & 1/2 < t < 1 \\ 0 & \text{Otherwise} \end{cases} \qquad (5.9)$$

Its scaling function Ψ(t) can be described using Equation (5.10)

$$¤(t) = \begin{cases} 1 & 0 \le t < 1 \\ 0 & \text{Otherwise} \end{cases} \qquad (5.10)$$

In functional analysis, the Haar system denotes the set of Haar wavelets

$$\{t \rightarrow \Psi_{n,k}(t) = \Psi(2^n t\text{-}k) \quad \text{where } n \in N,\ 0 \le k < 2^n\} \qquad (5.11)$$

In Hilbert space terms, this constitutes a complete orthogonal system for the functions on the unit interval (Gilbert, 2001). The Haar system (with the natural ordering) is further a Schauder basis for the space $L^p[0,1]$ for $1 \leq p < \infty$. This basis is unconditional for $p > 1$.

The Haar wavelet is the simplest possible wavelet with low computations and efficient memory usage characteristics. The technical disadvantage of the Haar wavelet is that it is not continuous, and therefore not differentiable. This property can, however, be an advantage for the analysis of signals with sudden transitions, such as edge breakage (Lee and Tarng, 1999), as is the case of fabric defect detection.

C) Optimal Tree Structure for Wavelet Decomposition

Consider for example, an image decomposed to three levels. This will result with 64 subimages. As the number of levels increases, the number of sub-images also increases. Thus, in order to enhance the process of decomposition, Jiang *et al.* (2009) proposed a method that can find an optimal decomposition of wavelets using wavelet tree structure. Tree structured wavelet transform is designed to get most significant information of a texture often appears in the middle frequency subband. Tree-structured wavelet transform determines important channels dynamically according to the energy calculation and can be viewed as an adaptive multichannel method. This method has the advantage of not completely decomposing all subimages and instead uses a criterion to decide on optimal level of decomposition of wavelets. The procedure used is presented in Figure 5.10. In this procedure, the size of the subimage is used as a stopping criterion for further decomposition. The smallest subimage that has been used in this work is 16x16.

- Apply Haar wavelet decomposition to obtain four subimages (LL, LH, HL and HH)
- Consider the sub-images obtained from Step 1 as nodes of the tree structure
- Calculate energy value of each subimage using Equation (5.12)

$$E_i = \frac{1}{N} \sum_{j.k=1}^{N} S_i(j,k)^2 \qquad (5.12)$$

  where E_i is the energy measure for subimage S_i and is the total number of pixels in the subimage.
- If energy value of some sub-image obviously smaller than other sub-images,

    then

        stop the process of decomposition else continue with the decomposition of other subimage

    else

        If the energy of a subimage is larger, then the above decomposition is applied to that subimage.

Figure 5.10 : Optimal Tree Structure for Wavelet Decomposition

D) Gabor Wavelet Network

Krueger and Sommer (2000) proposed the concept of Gabor wavelet network (GWN) to combine the advantages of wavelet networks (Zhang and Benveniste 1992) and Gabor wavelet decomposition. A GWN is a three layer wavelet network which uses the imaginary part of a Gabor function as the transfer function of a hidden node. As a new object representation method, the GWN has various advantages, e.g., it is invariant to affine deformations (Krueger and Sommer 2000), the Gabor wavelets in the network can be used to extract the features of local image structures, and the precision of object representation can be adjusted simply by adding or deleting some wavelets in the network. Currently the GWN has been successfully applied in a variety of fields, including head pose estimation, face recognition, and defect detection. The GWN is a model-based approach for effective and efficient object representation. The use of Gabor wavelets in the GWN enables the coding of geometrical and textural object features.

Since the concept of a GWN is proposed with reference to the 2D case, the network is described only in the 2D case in the subsequent discussions. To define a GWN, a set of N imaginary Gabor wavelets $\psi = \{\psi_{m1}, \psi_{m2}, \ldots, \psi_{mN}\}$ are used as the transfer functions in the hidden layer, which can be described using Equation (5.13).

$$\Psi_{mi}(x,y) = \exp\left\{\begin{array}{l} -\frac{1}{2}\left[d_x^i\left(\left(x - t_x^i\right)\cos\theta' - \left(y - t_y^i\right)\sin\theta'\right)\right]^2 \\ -\frac{1}{2}\left[d_y^i\left(\left(x - t_x^i\right)\sin\theta' - \left(y - t_y^i\right)\operatorname{cose}\theta'\right)\right]^2 \\ \sin\left(d_x^i\left(\left(x - t_x^i\right)\cos\theta' - \left(y - t_y^i\right)\sin\theta'\right)\right) \end{array}\right\} \quad (5.13)$$

where i = 1, 2, …, N, t_x^i, t_y^i denote the translation parameters of the ith Gabor wavelet, d_x^i, d_y^i denote the dilation parameters, θ' is the orientation parameter, and m_i (= [$t_x^i, t_y^i, d_x^i, d_y^i, \theta'$]) is the parameter vector of the ith Gabor wavelet. If the orientation parameter is not included, Equation (5.12) is a product of a 1D Gabor wavelet oriented along the x axis and a 1D Gaussian function oriented along the y axis. The mapping form of a GWN in the 2D case is defined using Equation (5.14).

$$gwn(x,y) = \sum_{i=1}^{N}[w_i \psi mi(x,y)] + \overline{gwn} = \sum_{i=1}^{N}[w_i \psi(D_i\, R_i(x - t_i))] + \overline{gwn} \quad (5.14)$$

where x (= $\left(= \begin{bmatrix} x \\ y \end{bmatrix}, x, y \in \Re \right)$) is the network input vector, gwn(x, y) is the corresponding network output, the parameter $\overline{gwn}$ is introduced to approximate functions with nonzero averages, w_i is the network weight associated with the Gabor wavelet ψ_{mi} and $D_i = \begin{bmatrix} d_x^i & 0 \\ 0 & d_y^i \end{bmatrix}$, $R_i = \begin{bmatrix} \cos\theta' & -\sin\theta' \\ \sin\theta' & \cos\theta' \end{bmatrix}$ and $t_i = \begin{bmatrix} t_x^i \\ t_y^i \end{bmatrix}$ represent the dilation matrix, the rotation matrix and the translation vector, respectively. Figure 5.11 shows the general mapping form of a GWN with the dilation, translation and rotation parameters.

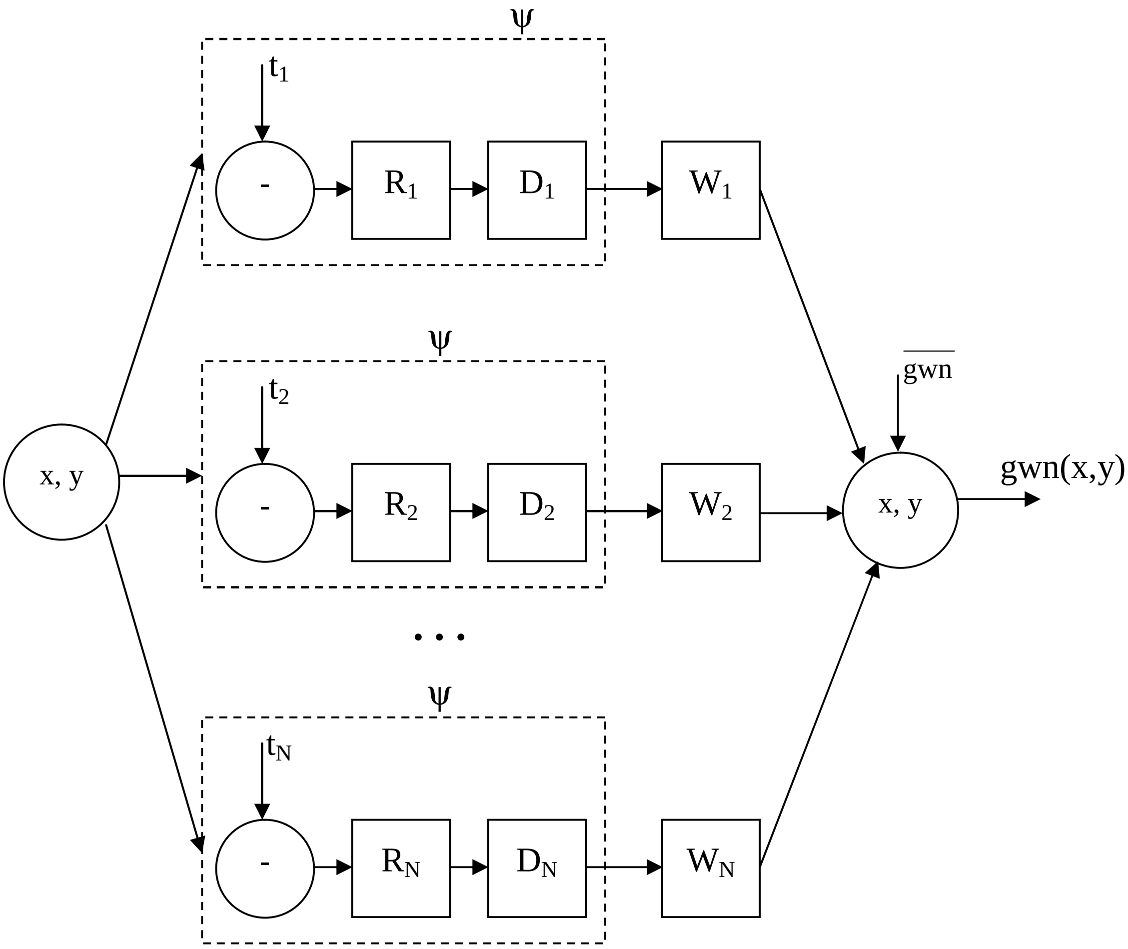


Figure 5.11 : Structure of Gabor Wavelet Network

In order to find an appropriate GWN to represent an objective function IM (e.g., an image), Gabor wavelets are added into the network one by one in Krueger and Sommer (2002). Whenever a new wavelet ψ_{mi} is added, the corresponding parameter vector m_i and weight w_i of the wavelet should be optimized at the same time. In the process of network optimization (network training), the energy function E defined in Equation (5.15) needs to be minimized.

$$E = \|IM - gwn\|^2 = \sum_x \sum_y \left[IM(x,y) - \sum_{i=1}^{J} [w_i \psi_{mi}(x,y)] - \overline{gwn} \right]^2 \quad (5.15)$$

The objective of the network optimization is to reduce the value of the energy function E , and to find an appropriate number of Gabor wavelets, and the corresponding parameters and weight of each wavelet, so that the resulting GWN can be used to effectively represent the objective function being studied. In this study, the GWN is used for extracting typical texture features (the basic yarn information) from the non-defective fabric image only requires one imaginary Gabor wavelet in the hidden layer. This reduces significantly the computational load needed in training the GWN.

5.3.3. Optimal Wavelet Coefficients Selection

In this step, two main selection techniques, namely, vector quantization (VQ) combined with Principal Component Analysis (PCA) and Independent Component Analysis (ICA) are first analyzed. These two techniques are then combined to achieve added advantage. The methods are explained in this section.

A) VQ + PCA Technique

Quantization is a many-to-one mapping that replaces a set of values with only one representative value. In the proposed VQ + PCA model, VQ of Kohonen Self Organizing Feature Map (KSOFM) is used. The following sub-sections introduce, VQ of KSOFM and PCA.

- **Vector Quantization of KSOFM**

There are two basic types of quantization,

(a) Scalar quantization and

(b) Vector quantization.

Scalar quantization (SQ) performs many-to-one mapping on each value, for example, it may store only the 6 most significant bits from 8 bit values. Vector Quantization (VQ) is the best way of quantizing and compressing images. It replaces arrays of values (i.e., blocks of pixels) with one value, which is the index from "codebook". The same index can be used to represent slightly different arrays of values; therefore it results in a lossy many-to-one mapping. The main implementation issues in the design of VQ algorithm is given below.

- Codebook design and storage of the codebooks in the image and
- Search Optimization - Computation complexity and time during the search for optimum code vector

When the codebook size is large, the reconstructed image will be very similar to the original image. At the other end, the image obtained using a small sized codebook will contain a lot of visible distortions. The size of the codebook is also important and has to be kept at a minimum. The storage of codebooks in the image is another important factor, which increases with the size of file.

The Kohonen network is a particular neural network and can be used as a vector quantizer for images. The results obtained by the Kohonen algorithm are acceptable, but the quality depends on the optimal parameters of the Kohonen networks. Vector Quantization has been observed as an efficient technique for image compression. The principle of the VQ techniques is simple. At first, the image is split into square blocks $X = \{x^1, x^2, x^3, ..., x^n\}$ of τ x τ pixels, for example 4 x 4; each block is considered as a vector in a 16-dimensional space, respectively, is used to generate a codebook $C = \{Y_1, Y_2, Y_3, ..., Y_N\}$ for the given set of image blocks.

Second, a limited number (N) vectors (codewords) in this space is selected in order to approximate as much as possible the distribution of the initial vectors extracted from the image; in other words, more codewords will be placed in the region of the space where there are more points in the initial distribution (image), and vice-versa. Third, each vector from the original image is replaced by the nearest codeword (usually according to a second-order distance measure). Finally, the index of the codeword is used instead of the codeword itself. Many authors used the Kohonen's Self-Organized feature Map (KSOM) to achieve the vector quantization process of image analysis. Kohonen's algorithm is a reliable and efficient way to achieve VQ and has shown to be usually faster than other algorithm.

- **Principal Component Analysis (PCA)**

PCA is a mathematical tool from applied linear algebra. It is a simple, non-parametric method of extracting relevant information from complex datasets. It provides a roadmap for how to reduce a complex dataset to a lower dimension. It is probably the most widely-used and well-known of the "standard" multivariate methods invented by Pearson (1901).

According to Jun *et al.* (2006) and Valarmathie *et al.* (2009), PCA is an unsupervised feature reduction technique which transformed high dimensional data to a low dimensional representation with minimum error rate, while maintaining the data variance that is important during data analysis.

Mathematically, PCA is defined as an orthogonal linear transformation that transforms data to a new coordinate system such that the greatest variance by any projection of the data comes to lie on the first coordinate (called the first principal component), the second greatest variance on the second coordinate, and so on. It transforms a number of possibly correlated variables into a smaller number of uncorrelated variables called principal components (Jolliffe, 2002).

PCs are calculated using the eigenvalue decomposition of a data covariance matrix/ correlation matrix or singular value decomposition of a data matrix, usually after mean centering the data for each attribute. Covariance matrix is preferred when the variances of variables are very high compared to correlation. It would be better to choose the type of correlation when the variables are of different types. Similarly the SVD method is used for numerical accuracy.

The transformation of the dataset to the new principal component axis produces the number of PCs equivalent to the number of original variables. In general, the first several PCs explain the most of the variances, so the rest can be eliminated with minimal loss of information. All PCs whose Eigen values are smaller than a fraction of the mean Eigen value are eliminated.

PCA is a relatively simple, non-parametric, generic method that is useful for finding new, more informative, uncorrelated points and can be used to reduce dimensionality by rejecting low variance points. Since the principal components are orthogonal to each other, every principal component is uncorrelated to every other principal component, that is, they do not contain any redundant information. The principal components are designed to account for the highest percentage of the variation among the variables with as few PCs as possible. Thus, often the first few PCs account for some large percentage of the total variance, allowing for a compact representation of the data with only low dimensions.

- **VQ + PCA**

In this technique, VQ of KSOFM and PCA are combined to obtain more optimal wavelet coefficients (Karras and Mertzios., 2002). Here, the coefficients obtained from wavelet variants (previous section) are first quantized using the vector quantization method of Kohonen Self Organizing Feature Map, which produces topology preserving codebook vectors (Haykin, 1999). These codebook vectors encode the topological space of the wavelet domain by preserving input vectors probability distribution and are estimated as the associated with the self-organizing map weight vectors. Let Cb_1, Cb_2, ..., Cb_n stand for these codebook vectors, where $n \ll r$, if r is the multitude of V_i input vectors, that span the corresponding wavelet domain.

For each such Cb_i, its corresponding autocorrelation matrix $Cb_i \times Cb_i^T$ is estimated and by applying PCA techniques the associated ratio $(\lambda_{min} / \lambda_{max})i$ is calculated for the minimum and maximum eigenvalues of this autocorrelation matrix. Such a ratio plays a significant role in expressing the properties of autocorrelation matrices and thus, to quantify the properties of the codebook vectors. All such $(\lambda_{min} / \lambda_{max})i$ calculated for every Cb_i, form the input feature vectors for the fault detection process.

B) Independent Component Analysis (ICA)

ICA is a method that transforms the observed multidimensional vector into its components which are maintained statistically as independent as possible. Independent Component Analysis (ICA) has emerged recently as one powerful solution to the problem of blind source separation.

ICA aims to find a linear transformation of the original data such that the new representation is one that minimizes the statistical dependence of the components present in the representation. ICA tries to find the hidden components that capture the essential structure of the data. The representation achieved by ICA facilitates the analysis of the data encountered in such fields like, data compression, pattern recognition, de-noising (Cohen *et al*., 1991).

The basic ICA model is shown as x = As and is the random vector containing the sources, and A is the mixing matrix (Sezer *et al.* 2004). No a priori information about the mixing matrix and sources are known. In order to make the problem of estimating the independent components by observing only the mixtures x solvable, the sources s must be assumed to be independent from each other with each having a non-Gaussian probability distribution. The sources s can be estimated after finding the de-mixing matrix B given in Equation (5.16).

$$s = Bx \qquad (5.16)$$

The demixing matrix can be estimated by maximization of the non-gaussianity of the sources. As the non-gausianity of the mixtures is increased, they become statistically more independent from each other (Ercil and Özüyılmaz, 1994). Hurri (1997) have presented some results in applying ICA to image data. The aim of ICA is to make the image pixels as mutually independent as possible.

An image subwindow I(x, y) can be represented as a linear sum of its basis functions (i.e., independent components) which can be extracted by ICA using Equation (5.17).

$$I(x,y) = \sum_{i=1}^{n} a_i(x,y)s_i \tag{5.17}$$

Here, $a_i(x, y)$ are called basis functions, and the s_i constitute the feature vector that will be used in the proposed defect detection system.

C) VQ + PCA + ICA

To further improve the defect detection process, the projection of VQ+PCA is further used in the realization of ICA algorithms on the coefficients obtained after the application of wavelets or Gabor wavelet. The process is illustrated in Figure 5.12.

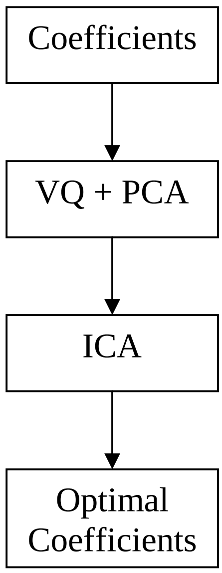


Figure 5.12 : Multiple Projection of VQ + PCA + ICA Procedure

5.3.4. Defect Detection Algorithms

The fabric fault detection in patterned fabrics is performed using two methods. The first method is based on Golden Image Subtraction combined with

Direct Thresholding (GISDT) and the second method uses a Neural-Network (NN) for fault detection. These two techniques are explained in this section.

A) GISDT Method

In the first step, the histogram equalization is performed on the input patterned fabric image to enhance the contrast of the image. If any m × n size subtracted image $H_{xy} = H_{xy}(i, j) = (h_{ij})$ from test patterned image P is subtracted from a golden image $G = (g_{ij})$ (image without defect) with size of m × n pixels (larger than one repetitive unit) from that reference patterned image F with size of M × N , then the energy of GIS is calculated using Equation (5.18).

$$R = (r_{xy}) = \frac{1}{mn} \sum_{i=1}^{m} \sum_{i=1}^{n} \left| g_{ij} - h_{ij} \right| \qquad (5.18)$$

where x = 1, …, M - m + 1 , y = 1, …, N - n +1 , i = 1, …, m and j = 1, …, n (0 < n £ N, 0 < m £ M) . The definition of energy of GIS aims to obtain the absolute difference between two images. The term $|g_{ij} - h_{ij}|$ is not squared due to simplicity. Also, the pixels of the images are in the range of [0, 1]. The squaring of the term will reduce the value which indicates the differences. The procedure of defect detection based on GIS method is given below and is illustrated in Figure 5.13.

1. Obtain a golden image $G = (g_{ij})$ of size m x n pixels (larger than one repetitive unit) from a reference patterned fabric image F of size MxN. The size of the repetitive unit is assumed to be obtained from the textile manufacturer or it can be obtained by using the correlation functions.
2. Perform the subtractions between the golden image $G = (g_{ij})$ of size m x n pixels and the subtracted image $H_{xy} = H_{xy}(i, j) = (h_{ij})$ of same size, by the definition of Energy of GIS, on the test image P from the first pixel to M - m+ 1th pixel of first row and go through second row and so on until N - n + 1^{th} row.

3. Return a (M - m+1) x (N - n +1) matrix, which is defined as a resultant image, R = (r_{xy}) by the energies of GIS.

- **Thresholding**

For a reference image, periodic hills and valleys will appear on the plot from the resultant image, R. A threshold image U = (uij) is defined as in Equation (5.19).

$$u_{ij} = \begin{cases} 1 \text{ if } r_{ij} > T \\ 0 \text{ if } r_{ij} \leq T \end{cases} \qquad (5.19)$$

where i = 1, …, M - m+ 1 and j = 1, …, N - n + 1 and r_{ij} is the energy value of resultant image R. T is the moderate threshold value. This image can be considered as a binary image and give the information on defects.

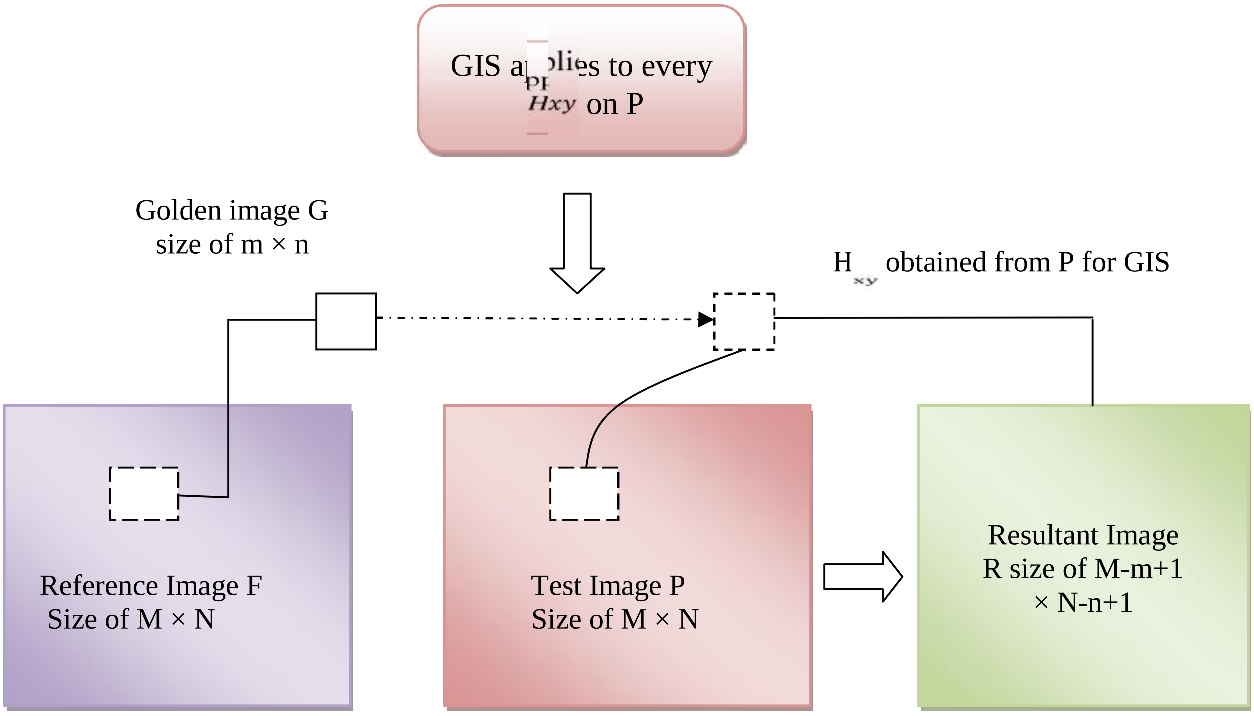


Figure 5.13 : GIS Method

A direct way to obtain the threshold value is to select the peak value of the hills from R of a reference image. For the defective samples, subtractions on the defective area will cause a distinguish jump that is quite different from the normal level. Hence, it will outline the defective region if an appropriate threshold value is used. Therefore, a training stage for obtaining the threshold value is essential.

The method to train the threshold value is first to collect a large amount of reference samples F_k where k = 1, …, w, that is, w reference samples. Using the same golden image, GIS is applied on every sample. So, if $T_k = \max(r_{xy})$ where x = 1,…, M - m + 1 and y = 1, …, N - n +1, the maximum value of energy of GIS of every reference sample for k = 1, …, w , is used as an indicator, then the defective regions are segmented out.

In this study, a direct thresholding method that automatically determines the threshold, T, is used. A noise tolerance is given so that the highest portion for each T_k can be truncated. For example, the T_k can be 0.95 of the original peak value in R_k if there is a 5% noise. Afterward, averaging all the maximums (T_1T_2, …, T_w) will give the moderate threshold value T, where $T = (T_1 + T_2 + \ldots + T_w)/w$. Using this threshold value, the defective region can be found on a test image P.

- **Defect Detection**

After obtaining the threshold value T, the steps in Figure 5.14 is used for detecting the defects. This method uses the traditional exclusive OR operation (XOR) as image subtraction method for defect detection

Figure 5.14 : XOR Based Image Subtraction for Defect Detection

B) Neural Network Based Segmentation of Defective Areas

After obtaining the wavelet domain based characteristics of each M x M sliding window raster scanning the N x N image, involving the above defined methodology, a supervised neural network architecture using MultiLayer Perceptron, having as goal to decide whether such a sliding window covers a defective area or not. The inputs to the network are the 16 components of the feature vectors extracted from each such sliding window as previously defined.

The desired outputs during training are determined by the corresponding sliding window location. More specifically, if a sliding window belongs to a defective area the desired output of the network is one, otherwise, it is zero. A defective window during MLP training phase is defined as a sliding window belongs to a defective area if the majority of the pixels in the 4 x 4 central window inside the original 32 x 32 corresponding sliding window belongs to the defect. The reasoning underlying this definition is that the decision about whether a window belongs to a defective area or not should come from a large neighborhood information, thus preserving the 2-D structure of the problem and not from information associated with only one pixel (e.g the central pixel).

In addition and probably more significantly, by defining the two classes in such a way, many more training patterns for the class corresponding to the defective area can be obtained, since defects, normally, cover only a small area of the original image. It is important for the effective neural network classifier to have enough training patterns for each one of the two classes but, on the other hand, to preserve as much as possible the a priori probability distribution of the problem. Empirically, it was found that a proportion of 1:3 for the training patterns belonging to defective and non-defective areas respectively is very good for achieving both goals. The steps involved are presented below.

- The N x N image is raster scanned by M x M sliding windows
- Each such window is transformed into the wavelet domain to obtain its corresponding coefficients

- Starting from the channel LLK (the Low Pass filtered image obtained using K level decomposition), the multidimensional vectors Vj are formed from the coefficients for each subband.
- Use VQ + PCA or ICA or VQ + PCA + ICA to obtain optimal coefficients
- Calculated (λmin / λmax)I and use them to train and test the network

5.3.5. Post-Processing

After detecting the faults using the above procedures, there will exist some white impulse noise. A filtering technique on threshold image D is needed in order to remove the noise and enhance the defect detected image. For this purpose, the denoising algorithm presented in Phase I of the study (Chapter 4) is used.

In this chapter, two groups of non-motif based techniques, one based on image data fusion technology and another based on wavelets were discussed. The next chapter (Chapter 5) discusses the proposed enhanced motif-based algorithm for fault detection in patterned fabrics.