3. METHODOLOGY

Digital image processing techniques have been increasingly applied to textured sample analysis over the past few years. Regularity is one of the most important features in many textures including patterned fabrics (Konda *et al.*, 2012), which as mentioned in previous chapters, is built on a repetitive unit of pattern. Wallpaper fabric, a part of patterned fabric, is a decorative material covered with fabric or other natural fiber materials. Wallpaper fabrics are different from other indoor decorative materials and are designed for daily use with easy maintenance instructions. As a consequence to this demand, fault detection and recognition used for quality assurance in wallpaper fabrics is considered important.

Textile production, initially a man-made task, is now a factory system and mass production. Today, the manufacture of textiles includes processes such as spinning, weaving and the finishing of products. The global textiles and garments industry has become an important trade worldwide. Technological breakthroughs envisaged both in manufacturing machineries and manufacturing methods have increased the demand for quality fabrics worldwide. Patterned fabrics, especially wallpaper fabrics, are complex, high-tech trades invested with numerous competitive challenges.

This research study, in order to meet the objectives outlined in Chapter 1 (Introduction), focuses on the design and development of fault detection systems on patterned wallpaper fabrics. This chapter introduces the various steps of the proposed system and outlines the methodology proposed in each step.

3.1. PROPOSED FAULT DETECTION ARCHITECTURE FOR PATTERNED FABRICS

The present research work proposes new algorithms based on the effective, synergistic integration of several schemes that aim to achieve maximum efficiency during fault detection in terms of speed and accuracy. New techniques are proposed because of the following reasons :

- Researchers should always challenge industrial standards by developing new competitive methodologies.

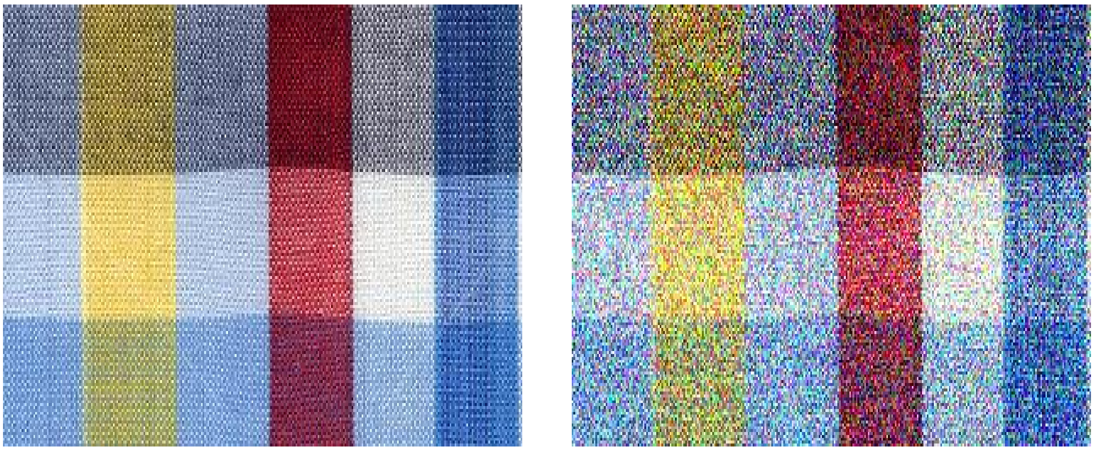
- Owing to the wide usage of computer aided systems, several textile industries require techniques that meet the competitive and cost effective requirements of modern fault inspection tools.

While considering methods to improve existing works, methods that combine the advantages of various techniques have gained more attention. The solutions provided in this research work are more compatible for wallpaper groups of patterned fabrics but can also be analyzed for other type of patterned fabrics.

Patterned texture defect detection is a traditional topic which has been researched for many years. Broadly, methods can be classified as non-motif-based and motif-based methods. As fault detection in patterned fabric is more challenging than regular fabrics, this study designs and develops both motif-based and non-motif-based methods for detecting faults in patterned fabrics.

As observed from previous implementations of fabric inspection systems, it is necessary to consider the following factors during the design and development of automatic fault detection systems for patterned fabrics.

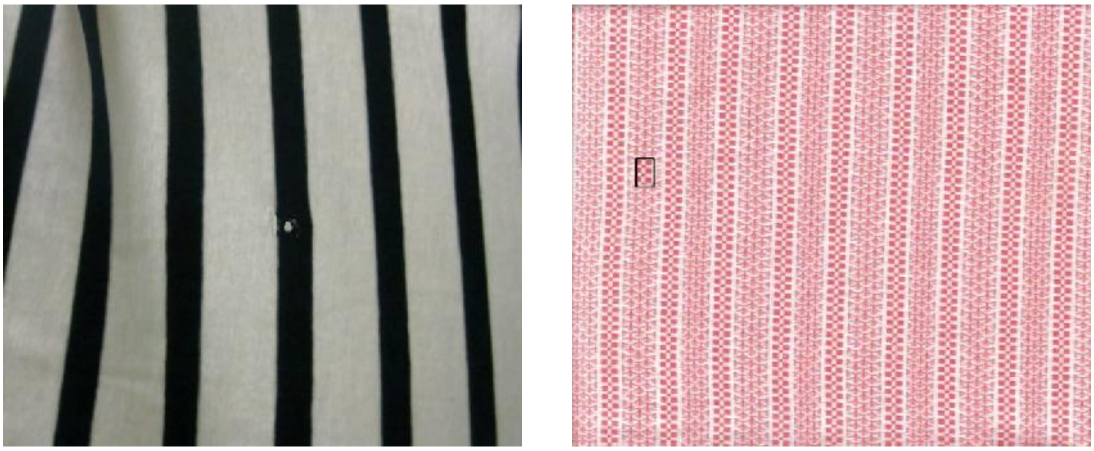
1. Quality of input image. Factors like noise, contrast variation, are known to increase misclassification rates. Figure 3.1 shows an example where noise in fabric (Figure 3.1b) is obscuring the original pattern of the image (Figure 3.1a).



(a) **(b)**

Figure 3.1 : Example of Noise Obscuring Fabric Background Pattern

2. Size and shape of defects : Defect of small size or defect similar to a pattern shape increases difficulties during fault recognition). An example of small sized defects and defect similar to pattern is shown in Figure 3.2a and b respectively.



(a) **(b)**

Figure 3.2 : Small Sized Defect and Defect Similar to Pattern

3. Speed of defect detection : Longer duration for detecting faults is not a desirable property in textile industries.

Generally, there is always a trade-off between the different characteristics in the design of a defect detection method. There is no doubt that a proper assessment and balance of each characteristic would likely lead to a more satisfactory detection success rate. In the present study, the first problem is solved by using a denoising algorithm. To evaluate the proposed fault detection algorithms on varying defect sizes and shapes, man-made faults (dirt) are introduced and experiments are conducted to analyze their effects on detection accuracy.

All the proposed methods considers the above mentioned issues of the existing system and designs the fault detection system using five steps (listed below) after image acquisition. Figure 3.3 presents the architecture of the proposed fault detection methods for patterned fabrics.

1. Preprocessing
2. Extract Pattern components (wavelets, lattices, motifs)
3. Extract features (coefficients, variance and energy)
4. Defect identification - Classify fabric as “defective” or “defect free” fabric
5. Defect Recognition - Locate defect region

As motifs of a patterned texture contain finer details than lattice and exhibit symmetry property, given a lattice (which contains a number of motifs in general), the differences between the circularly-shifted copies of the lattice and itself characterizes the lattice (and the motifs) uniquely. If a defect exists in the lattice, then the characterization is affected or changed such that the defect can be identified by comparing the defective characterization against the defect-free characterization. Figure 3.4 shows various examples of patterned fabrics along with its lattices and motifs.

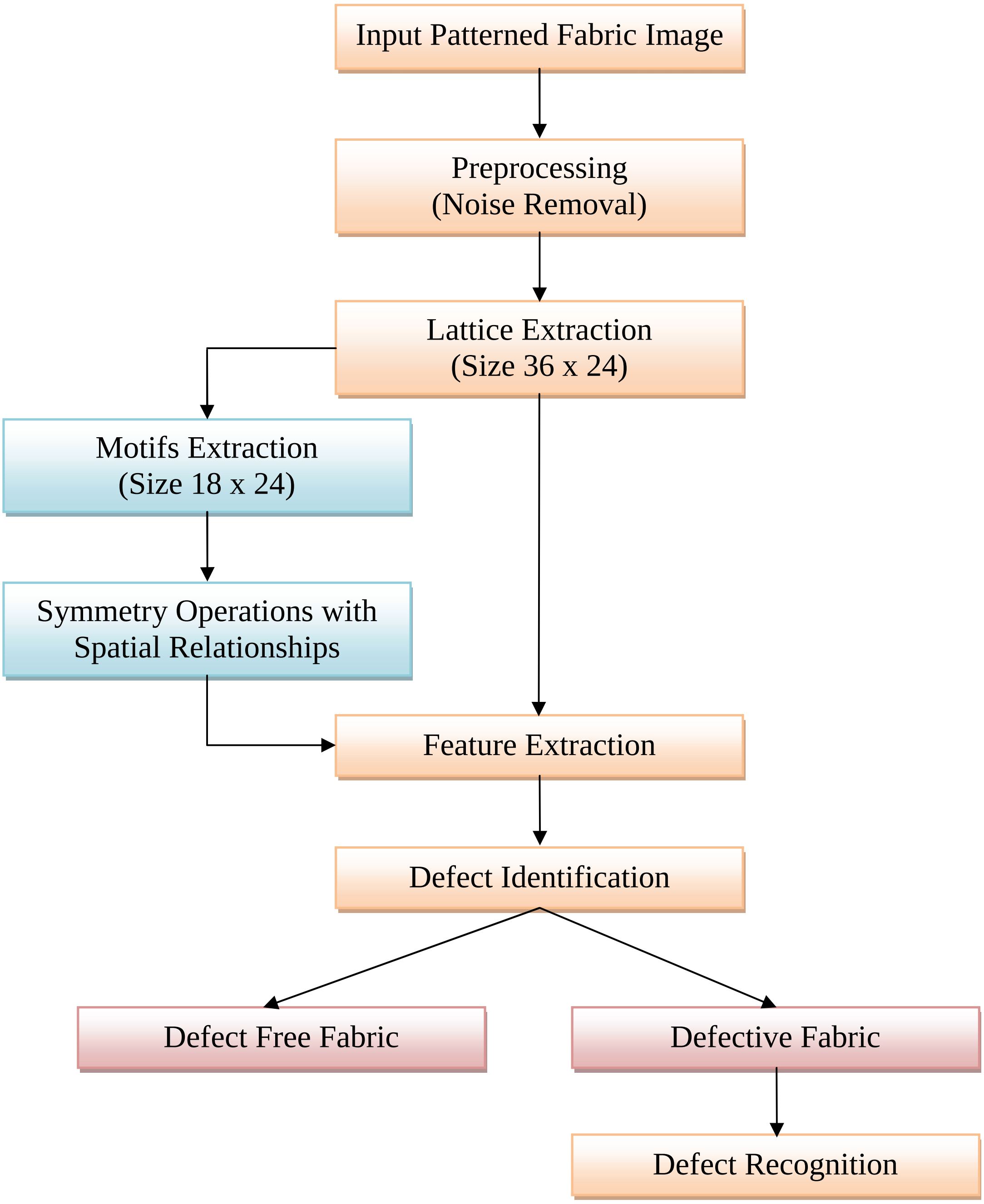
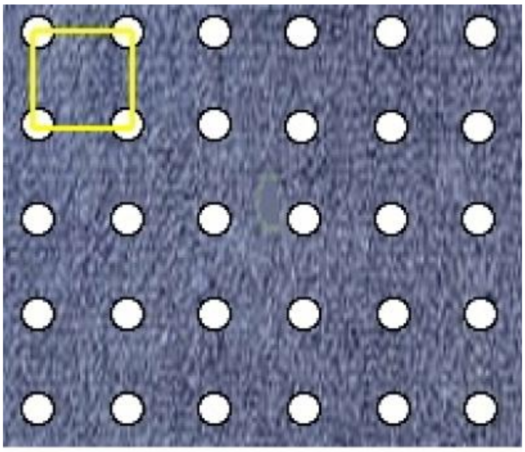
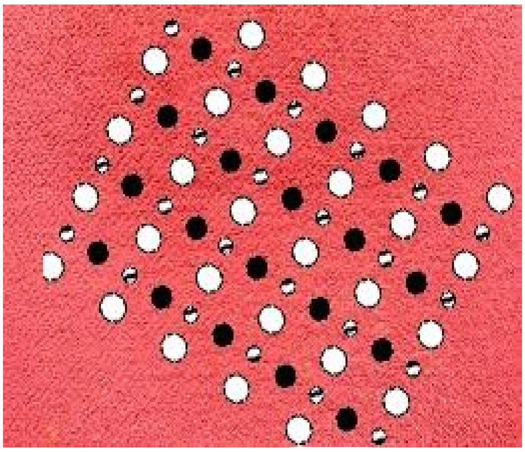


Figure 3.3 : Proposed Patterned Fabric Fault Detection Architecture



Motif → ○

a) Square Lattices and Motif



Motif →

b) Parallelogram Lattices and Motifs

Figure 3.4 : Patterned Fabrics with Lattices and Motifs

3.2. PROPOSED METHODOLOGY

The study, as mentioned previously, focuses to propose both motif and non-motif based techniques for fault detection in patterned fabrics. For this purpose, the research design (Figure 3.5) is framed as three phases as follows.

- Phase I : Preprocessing of Patterned Fabric Image
- Phase II : Non-Motif Based Models
- Phase III : Motif Based Model

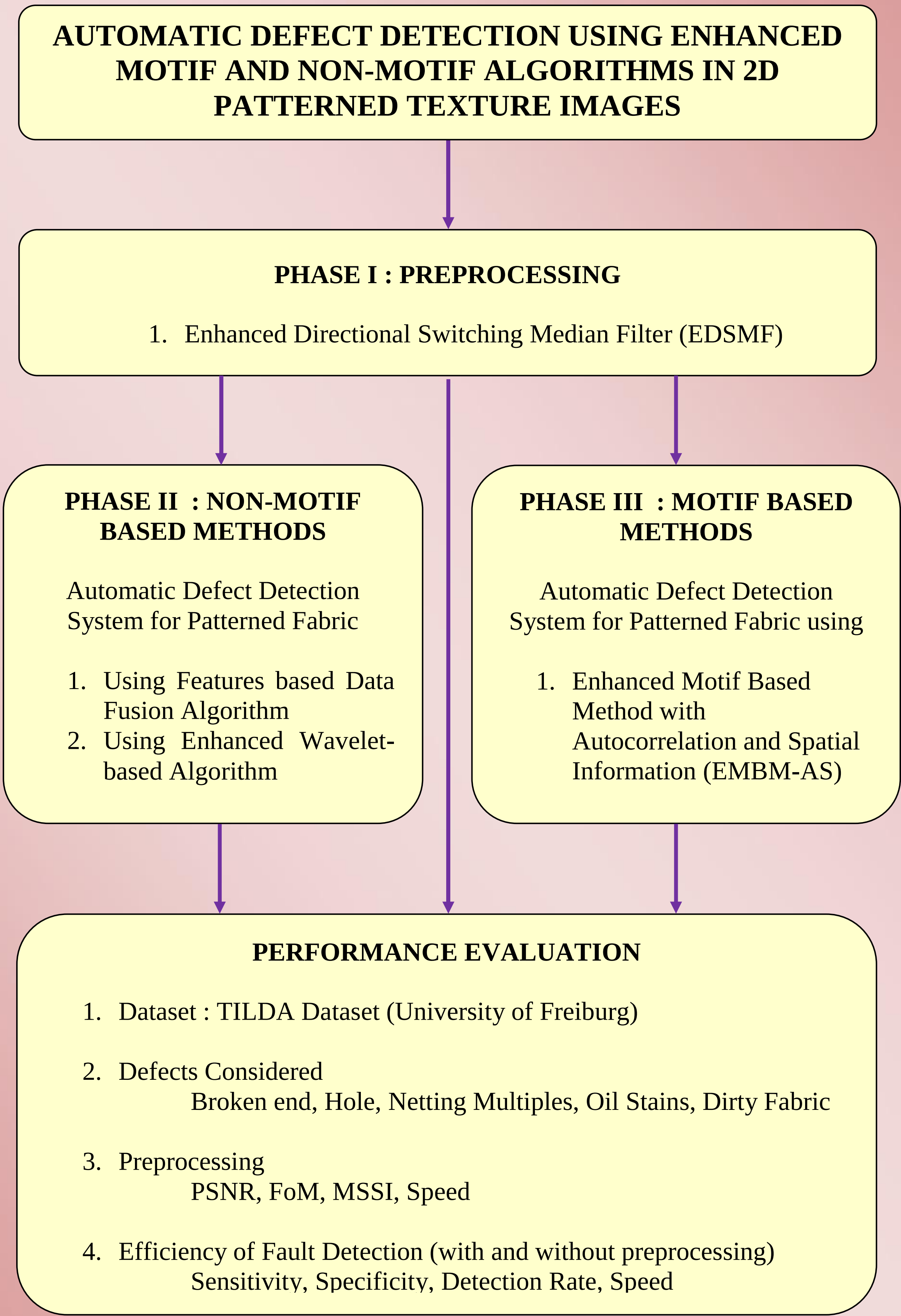


Figure 3.5 : Research Methodology

3.2.1. Phase I: Preprocessing

Preprocessing phase of automatic defect detection in patterned fabrics proposes the use of various algorithms that enhances the quality of the input patterned fabric 2D images in order to increase the efficiency of the subsequent processes of fault detection. One main factor that destroys the quality of fabric images is the presence of noise.

The search for efficient image denoising methods still is a valid challenge in the field of textile images, at the crossing of functional analysis and statistics. Even in the presence of the sophistication of the recently proposed methods, several of the existing algorithms have not reached the desirable level of applicability with fabric images. Most of these algorithms demonstrate an excellent performance when the image model corresponds to the algorithm's hypothesis, but fails in general and removes image structures.

The study processes an Enhanced Directional Switching Median Filter (EDSMF) which is designed to remove the presence of Salt & Pepper noise in the 2D patterned fabrics. As Salt & Pepper noise appears as bright dots or dust particles and is normally distributed randomly all over the image, often they are miss-diagnosed as defects and hence, have to be removed before detection and recognition processes. The EDSMF algorithm consists of the following steps.

1. Noise detection using enhanced directional detector from the noisy 2D patterned image

2. Separate noisy and noise free pixels

3. Perform modified adaptive switching median filter to remove noise

The noise detection algorithm considers a sliding window of size 3 x 3, from which the Sum of Intensity Distance (SID) and the Sum of Angular Distance (SAD) are calculated in the four diagonal directions. The SID is based on the brightness value of a pixel, while the SAD is calculated using the arcos between two pixels. Using the minimum SID and SAD values along with two thresholds (T1 and T2) are then used to identify the noisy pixels. Both T1 and T2 are calculated using the genetic algorithm proposed by Goldberg (1989).

The genetic-based threshold calculation algorithm has the drawback that when the noise is uniformly distributed, both T1 and T2 are very high. It is a well-known fact that high threshold values cannot detect noisy pixels correctly and often misclassify them as noise free pixels. Hence, an additional third threshold (T3) is used by the proposed algorithm. This threshold aims to detect maximum noisy pixel while preserving all noise free pixels. The threshold T3 is calculated by sorting the pixels in the windows in ascending order of intensity excluding the central pixel. The third threshold is connected with the Intensity Strength (IS) of a pixel during noise detection and is calculated using the method proposed by Kang and Wang (2009). Equation 3.1 presents the noise detection step used by EDSMF.

$$B_{ij} = \begin{cases} 1 & |IS(x_{ij}) - IS(median(x_{ij}))| > T3 \;\&\&\; min_{SID} < T1 \;\&\&\; min_{SAD} < T2 \\ 0 & otherwise \end{cases} \tag{3.1}$$

where B_{ij} is a binary image representing the result of noise detection.

The next stage of the algorithm considers the binary image from the previous step and performs median filtering only on the noisy pixels. The algorithm iteratively considers each pixels and switches to a filtering mode, when a noisy pixel is encountered. The traditional switching algorithm is enhanced where, the sliding window size during the iteration of switching median filter is adaptively determined.

Chapter 4, Design of Preprocessing Algorithm, provides the detailed description of this algorithm and the experiments conducted to evaluate the performance of the proposed algorithm is presented in Chapter 7, Results and Discussion.

3.2.2. Phase II: Non-Motif-Based Methods

The second phase proposes Non-Motif-Based Method for solving the problems in patterned fabric fault detection. Two methods, as listed below, are proposed.

A. Automatic defect detection using image data fusion

B. Automatic defect detection using enhanced wavelet-based algorithm

A Automatic Defect Detection using Image Data Fusion Algorithm

Image data fusion is a technique that is used to combine different image data or features obtained by analyzing the image using decision making rules (Yuan *et al.*, 2006). The algorithm as a first step performs wave profile analysis, examines information in the wave profile of the intensity curve for every line of pixels. Local distortions of the wave profile indicate information of defect and defect free regions. The common characteristics of the wave shape include the gradient, local maximum, mean and variance of the curve. A segmentation based on dynamic thresholding method is then used to identify the defects in intensities. In the second step, a sobel edge detector is used to extract edge details of the images. The results obtained from first and second step are then fused by using an intersection operation, to identify defects in the input 2D patterned fabric image.

B Automatic Defect Detection in using Enhanced Wavelet-Based Algorithm

The algorithms proposed in this section amalgamates techniques like histogram equalization, wavelet transformation, golden image subtraction (GIS), Independent Component Analysis (ICA) along with neural networks to identify defective regions in the 2D patterned fabric image. The histogram equalization is performed to enhance the contrast. This is followed by the application of any one of the two wavelet transformations namely optimal tree structured wavelet transformation and Gabor Wavelet Network. To select optimal coefficients from the above step, three techniques are used. The first method combines Vector Quantization (VQ) with Principal Component Analysis (PCA), the second is Independent Component Analysis (ICA) and the third combines both these techniques.

For defect detection two algorithms are used. The first is enhanced Golden Image Subtraction (GIS) with Direct Thresholding (DT) and the second uses neural network. In GIS-DT method, the golden energy of each subband is calculated. If the energy value of a sub-image is smaller than other subimages, the decomposition process is stopped. Comparison of these values with a defect free image identifies the defects in the fabric. In the neural network based model, a MultiLayer Perceptron (MLP) is trained to identify and segment defective regions in the input patterned fabric image. In order to remove the noise introduced by the threshold operation, a smoothening processing using the denoising technique proposed in Phase I is again applied.

Thus, Phase II of the study proposes the following models.

1. Automatic Defect Detection using Image Data Fusion Algorithm
2. Automatic Defect Detection using optimal wavelet tree based GIS Algorithm using VQ + PCA projections
3. Automatic Defect Detection using optimal wavelet tree based GIS Algorithm using ICA projections
4. Automatic Defect Detection using optimal wavelet tree based GIS Algorithm using VQ + PCA + ICA projections
5. Automatic Defect Detection using optimal wavelet tree using VQ + PCA projections on Neural Network
6. Automatic Defect Detection using optimal wavelet tree based using ICA projections on Neural Network
7. Automatic Defect Detection using optimal wavelet tree based using VQ + PCA + ICA projections on Neural Network

8. Automatic Defect Detection using Gabor wavelets based GIS Algorithm using VQ + PCA projections
9. Automatic Defect Detection using Gabor wavelets based GIS Algorithm using ICA projections
10. Automatic Defect Detection using Gabor wavelets based GIS Algorithm using VQ + PCA + ICA projections
11. Automatic Defect Detection using Gabor wavelets using VQ + PCA projections on Neural Network
12. Automatic Defect Detection using Gabor wavelets based using ICA projections on Neural Network
13. Automatic Defect Detection using Gabor wavelets based using VQ + PCA + ICA projections on Neural Network

The working of the various non-motif methods proposed for detecting faults in patterned fabrics are presented in detail in Chapter 5, Design of Non-Motif-Based Algorithms. The efficiency obtained by the proposed algorithms over the existing solutions are presented and discussed in Chapter 7, Results and Discussion.

3.2.3. Phase III: Motif-Based Methods

Motif-Based Method (MBM) uses lattices and their constituents, motif, for defect detection in patterned textiles (Ngan *et al.*, 2008).The proposed methodology consists of six major steps. The algorithm begins by extracting the lattices manually. From each of these lattices, the next step extracts the motifs. Circular shift matrices of these motifs are constructed from which the energy and variance are calculated. From these values, the decision boundaries are determined using E-V plot. Once the boundaries are determined, the proposed methodology can be used to discern defective lattices from defect-free lattices. In addition, the E-V points that fall outside the boundaries indicate which motif is being defective. The MBM consists of the following two issues.

- Issue 1 : Template image is created by manually extracting lattices from database.
- Issue 2 : The circular shift operation used ignores the spatial relationships among the pixels in order to neglect the effects of slight distortions on the lattices.

The first issue is solved in the present research work using automatic process called Autocorrelation Algorithm. Through local histogram analysis experimentation, it was found that motifs on defective lattices being misclassified (false negative) as the histograms of defective motifs are very similar to those of defect-free ones. This is because, the spatial relationships between pixels are found to be weak under the definitions of energy of moving subtraction and its variance. This results in similar histograms between a small number of defect-free and defective motifs.

Therefore, there is a need to develop a complimentary approach on the existing method in order to retain some spatial relationships among the pixels in the motifs. The second issue is thus solved by combining spatial relationships between pixels. The problem will be solved because distortions are removed in preprocessing step. The proposed model is thus termed as Enhanced Motif based Method with Autocorrelation and Spatial Information (EMBMAS).

Detailed description on the working of the proposed motif-based fault detection algorithm is presented in Chapter 6, Design of Motif-Based Algorithm and the experimental results comparing the performance of the proposed algorithm with the existing algorithm, to analyze the efficiency obtained by the proposed motif-based algorithm, is presented in Chapter 7, Results and Discussion.

3.2.4. Experimental Results

During experimentation, 600 images consisting of both defective and defect-free images were collected. During experimentation, five types of defects were considered, namely, broken end, hole, netting multiples (manufacturing detects), oil stains and dirty fabric (human made defects).

The experiments were conducted in four stages. The first stage evaluates the performance of the denoising algorithm using four performance metrics, namely, Peak Signal to Noise Ratio, Figure of Merit, Mean Structural Similarity Index (MSSI) and speed. The second and third stages were devoted to analyze the non-motif and motif based algorithms proposed in Phase II and III. The metrics used during second and third stage of performance evaluation are sensitivity, specificity, detection rate and speed. The fourth stage of experiments is devoted to find the algorithm that performs best among the proposed motif and non-motif based algorithms.

Experimental results proved that all the proposed models show improvement in performance when compared to the existing wavelet based, GIS-based and MBM models. Among all the proposed models, the EMBMAS method shows high performance efficiency in terms of the metrics selected. Among Phase II models, the method that used wavelets with VQ and PCA produced better results. A maximum of 95.99% was achieved by EMBMAS model while detecting broken fabric defect. The wavelet model combined with VQ and PCA achieved maximum detection rate (93.34%) which showed an efficiency gain of 4.29% when compared to the existing wavelet based model. All the proposed algorithms are very efficient in identifying broken defect, followed by hole, netting multiples, oil stains and dirty fabrics.

The tables and graphs supporting the above results are presented in Chapter 7, Results and Discussion.

The proposed research aims to design and develop automatic defect detection system for patterned fabrics in two steps, namely, preprocessing and defect identification. The algorithms are designed in a manner that they enhance the defect detection and recognition process. The two steps are interrelated, where the output of the first step is treated as input to the second step. This chapter introduced the design methodology and various techniques proposed in each of these steps. The next chapter (Chapter 4, Design of Preprocessing Algorithm) presents the enhancement algorithm used during the design of proposed fault detection architecture.