Chapter 3

GREY FABRIC DEFECT DETECTION (GFDD) Part-I

3.1 Introduction

The objective of the Grey Fabric Defect Detection (GFDD) is to identify and classify the commonly occurring microstructure grey fabric defects. We have focused on detection of such defects occurring in shirting and suiting material during weaving process besides the other defects being attempted by others as per the literature review. The image processing techniques for defect detection are basically based on texture analysis described in Chapter 2. We have carried out texture analysis in spatial as well as in frequency domain to understand the performance of the methods for each domain. Different modules are developed in each domain for analysis. In this chapter besides the experimental details of the experiments performed by us, the theoretical details are also presented wherever required with relevant references from the literature. The details of the research work carried out are presented in the form of work flow in the following section.

3.2 Research Work Flow of Grey Fabric Defect Detection

The work flow of our research is divided into three parts (Part-I), (Part-II) and Part-III as shown in Figure 3.1. Part-I corresponds to the preliminary work of preparation of raw data base followed by preprocessing, application and testing of traditional methods viz., Morphological Approach (MA) and Correlation
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Approach (CA) and a new Hybrid Approach (HA) of combining of both the spatial domain and frequency domain method which is suggested by us.

![Work Flow Organization](image)

Figure 3.1: Work Flow Organization

The details of Part-I are presented in this chapter. Part-II presents the details of application of Fourier transform and Fourier Power Spectrum (FPS) for GFDD besides highlighting the pros and cons of these two methods leading to the use of novel DC suppressed FPS sum approach viz., DCSFPSS for determination of periodicity of fabric texture and hence for finding the fabric quality parameter viz., thread count which is presented as an outcome. Exploration of novel DCSFPSS for modification of MA, CA methods and HA for defect detection are explained in Chapter 4. Part-III of work flow consists of frequency domain method for classification of fabric defects using the new feature set extracted from DCSFPSS. This forms the major contribution of the research work. The details of defect classification using new novel Fourier transform based features by a supervised classifier and results of feature
robustness testing using Principal Component Analysis (PCA) are presented in Chapter 5.

a. Details of Work Flow Part-I

As seen from the work flow Part-I of Figure 3.2, at the primary stage of Part-I, collection of ample of plain and twill weave normal and defective samples from industry was done to generate image data base.

![Diagram](image)

Figure 3.2: Work Flow Part-I

The entire image data-base created for this research work includes the industrial sample images as well as the patterns generated through programs and simulated weave patterns. The industrial samples were imaged using Zeiss stereomicroscope imaging equipment. The standardization of the Zeiss stereomicroscope for image resolution, illumination focus and magnification was carried out carefully. As per the work flow Part-I of Figure 3.2, all the industrial samples were converted from RGB to gray images first and were subjected to image preprocessing. This workflow is broadly classified into three different approaches for GFDD viz., spatial domain analysis, frequency domain
analysis and hybrid approach. The well accepted researched method in the spatial domain is the Morphological Approach (MA). It is the simple approach for segmentation of defect region from non-defect region using structuring element which acts as a filter for retaining region of defect. The work on this method indicated that GFDD is a strong function of selection of type and size of structuring element.

For frequency domain analysis, i.e. Correlation Analysis (CA) was experimented on both plain and twill weave fabric defects. In the correlation analysis, template matching method was implemented using suitable template (which acts as a window for identifying the region having maximum correlation) for each type of defect. Similar to the result of MA, here also the dependency of correlation method on selection of type, size of defect template and the value of thresholding was observed.

To overcome the drawbacks of MA on plain weave fabric defects, a hybrid approach viz., CA using defect template followed by MA was implemented on all plain and twill weave defects. This method was found to outperform when compared to the individual approaches applied independently. However it was found that, it needs modification for automatic selection of template independent of defect pattern and for size of structuring element. The details of the above three approaches are given in the following sections.

3.3 Experimental Set up for Image Data Base Preparation

3.3.1 Introduction

The focus of this research was on identifying the grey fabric defects occurring commonly on fabric weaved on air jet and rapier auto-loom. Samples of grey fabric shirting and suiting without and with defects generated during weaving were collected from Jathar Textiles, Ichalkaranji. Two weaving patterns viz., plain weave and twill weave patterns and their real time defects were considered for research. The other patterns used for initial phase of work were
generated patterns through MATLAB/Paint brush such as horizontal stripes, vertical stripes and diagonal stripes, checks and huckbuck patterns. Simulated real plain and twill patterns obtained from net and Tex-card generated textile weave patterns also were part of the data base.

The selection of the image resolution for GFDD inspection is largely dependent on the available computational power and expected performance. Major fabric defects in the images of defective samples can be detected using low and medium resolution images. However subtle fabric defects are those which are not visible during post weaving checks but become visible after the fabric is subjected to chemical processing. A high resolution image is recommended for such subtle defect detection [1]. The quality of acquired image plays a vital role in defect detection. The image quality is drastically affected by the type and level of illumination. But the effective performance evaluation requires the careful selection of the data set with its clear definition of scope to remove the subjective judgment of results.

To meet the objective of detecting the micro-nature defects and further to improve accuracy of detection, instead of obtaining images from a normal imaging camera with simply higher resolution of the order of 10 to 15 megapixels, we selected an imaging device with attached optical section for image zooming and grabbing information without loss or modification of small and fine details. Thus to detect the defects of real fabric, Zeiss Motorized Microsterioscope with optical magnification of 12x was used as an imaging device. This microscope is designed, produced and tested in compliance with the standard DIN EN 61010-1[B14]. The imaging equipment is as shown in Figure 3.3 and its specifications are detailed in the next section.

3.3.2 Steriomicroscope Details and Image Acquisition

Stereo Discovery V12, Steriomicscopes shown in Figure 3.3 is a microscope designed for 3-D observation of small objects. This is designed
according to the telescope principle with both optical paths using a common main objective.

![Image of imaging system used for grey fabric defect detection](image)

**Figure 3.3: Imaging System used for Grey Fabric Defect Detection**

It features high optical image quality. The pancreatic magnification changer ensures high contrast, focused images throughout the entire zoom range. After the basic adjustment of the stereomicroscope, the image remains exactly in the focus. Progressive light source and illumination can be continuously adjusted by electronic control separately for cold light source (KL1500 LCD), thus following the illumination to be adapted to most diverse objects. The magnification ranges from 5x to 60x with object field up to 30 mm with working distance of 80 mm between microscope and object. Optical magnification 12 x covers a magnification range from 0.8x to 10x. The 1.3 mega pixels “Pixel Linking Camera” has pixel size of 6 μm x 6 μm and has image resolution of (1280 x 1040) pixels. AXIO vision software is used for acquiring defective and defect free fabric images.

To prepare the image data base, images of the fabric samples were obtained after standardizing the motorised Zeiss stereomicroscope with magnification of 12 x, focus of 19 and depth, z of -1.45 mm. The glass slide consisting of standard ring with accurate fixed dimension provided by the manufacturer of the ZEISS Sterio microscope as shown in Figure 3.4 was used as a reference standard for
standardization. This was further used for calculating image width and length corresponding to area of fabric image exposed to imaging device. Image data base of plain weave samples and twill weave samples with the specifications of the fabric, the type of the defects and number of defect samples of each type of defect for each weave pattern are as shown in Table 3.1 and Table 3.2 respectively.

Figure 3.4: Standard Ring for Image Size Calibration

With these microscope parameter settings, the image area covered was 1.01cms x 0.81cms (on an average). This was found to be suitable for both plain and twill fabric subtle defect and defect free samples.

Table 3.1: Details of Plain Grey Fabric Samples under Study

<table>
<thead>
<tr>
<th>Sr. No</th>
<th>Plain weave fabric class</th>
<th>Plain Fabric Specifications</th>
<th>Defect Type</th>
<th>Number of Samples</th>
<th>Total samples/class</th>
</tr>
</thead>
</table>
| 1      | S₁                       | 132 x 120  
 60 x 60          | 1.Normal          | 274               | 486                |
|        |                          |                            | 2.Warpbreak    | 108               |                     |
|        |                          |                            | 3.Loose-weft   | 24                |                     |
| 2      | S₂                       | 124 x 64  
 30” x150D        
 Warp-30s cotton  
 Weft-150D micro | 1.Normal          | 275               | 517                |
|        |                          |                            | 2.Doublepick   | 147               |                     |
|        |                          |                            | 3. Loose-weft  | 95                |                     |
| 3      | S₃                       | 144 x 144  
 80 x 80          | 1.Normal          | 185               | 421                |
|        |                          |                            | 2.Doublepick   | 130               |                     |
|        |                          |                            | 3. Thick place | 116               |                     |
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Table 3.2: Details of Twill Grey Fabric Samples under Study

<table>
<thead>
<tr>
<th>Sr. No.</th>
<th>Twill weave fabric class</th>
<th>Twill Fabric Specifications</th>
<th>Defect Type</th>
<th>Number of Samples</th>
<th>Total samples /class</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>S₁</td>
<td>124×56 2/40 3×300D</td>
<td>1.Normal</td>
<td>170</td>
<td>249</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Warp-2/40 cotton Weft-300D micro</td>
<td>2.Loose weft</td>
<td>134</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>3.Stitch</td>
<td>70</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>S₂</td>
<td>124×56 20 3×300D</td>
<td>1.Normal</td>
<td>215</td>
<td>217</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Warp-20 cotton Weft-300D micro</td>
<td>2.Loose weft</td>
<td>142</td>
<td></td>
</tr>
</tbody>
</table>

**Details of Terminologies Related with Fabric Constructional specifications:**

The specification of fabric \( F_{sp} \) contains information on number of ends per inch \( (EPI) \) equivalent to per 2.5 cms in warp direction and number of picks per inch \( (PPI) \) equivalent to per 2.5 cms in weft direction and the count of warp thread, \( C_{warp} \) and count of weft thread, \( C_{weft} \) out of which the fabric is made. Generally the standard followed for representation of fabric specification in the following form.

\[
\frac{EPI \times PPI}{C_{warp} \times C_{weft}} \tag{3.1}
\]

**One count (English)\( (N_e) \):** One count of a thread is defined as number of 768 m of yarn weighing 454.54gms for cotton and is given by,

\[
N_{Tex} = \frac{590.6}{N_e} \tag{3.2}
\]

**Tex \( (N_{Tex}) \):** Tex is expressed as weight \( (w) \) in grams of 1000 m of yarn.

**Yarn diameter \( (d) \):** It is of importance for fabric quality. If circular cross section of yarn is assumed, then diameter, \( d \) of yarn can be obtained as below,

\[
A = \frac{volume(v)}{length(l)} \tag{3.3}
\]
For \( A = \frac{\Pi d^2}{4} \) equation for \( A \) gives, \( d = \sqrt[4]{\frac{4v}{\Pi l}} \) (3.4)

As \( l \) is fixed at 1000m and for cotton yarn of specific volume 1.1 cm\(^3\)/g, diameter of yarn is given by,

\[ d = \sqrt[4]{\frac{4 \times N_{\text{Tex}} \times 1.1}{1000 \times \Pi}} \] (3.5)

Equation (3.5) simplifies to, \( d = \sqrt{\frac{N_{\text{Tex}}}{26.7}} \) (3.6)

Equation (3.6) is very close to most of other fibers and multifilament yarns irrespective of material content but not for mono-filament and bulked yarns [B3].

Denier: It is a system used as the standard count for filament silk and most man-made fibers.

Denier number \((D)\): It refers to the weight in grams of 9000 m of yarn or filament and is expressed by,

\[ D = \frac{5315}{N_e} \] (3.7)

Sample Evaluation of Tex for twill fabric \( S_2 \) class:

\( S_2 \) class twill fabric considered has constructional specification details given by

\[ \frac{124 \times 56}{20^4 \times 300D} \]

First term in the denominator corresponds to the cotton warp count of 20\(^s\) and second term corresponds to the weft count of 300D. Tex (Ne) for warp is as computed below.

\[ N_{\text{Tex(warp)}} = \frac{590.6}{20} = 29.5 \] (3.8)

And Tex (Ne) for Denier weft is as computed as shown further.

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\[ N_{e(\text{weft})} = \frac{5315}{300} = 17.72' \]

and

\[ 300 \text{ Denier} = 17.72^8 N_e \] (3.9)

\[ N_{fex(\text{weft})} = \frac{590}{17.72^8} = 33.30 \] (3.10)

Diameter of warp and weft yarn computed from (3.6) is as below

\[ d_{\text{warp}} = \frac{\sqrt{29.5}}{26.72} = 0.2032\text{mm} \] (3.11)

\[ d_{\text{weft}} = \frac{\sqrt{33.33}}{26.72} = 0.2162\text{mm} \] (3.12)

3.3.3 Fabric Image samples.

Following are the representative sample images grabbed using the Zeiss motorized stereomicroscope with parameter settings mentioned in Section 3.3.2.

**a. Plain Weave Normal and Defective Samples**

Figure 3.5, 3.6 and 3.7 show the images of plain grey fabric with different fabric defects occurred during weaving.

![Figure 3.5: Plain Weave Sample Images of S1 Class](image)

a: Normal  b:Warp Break  c:Looseweft d: Coarse-weft

Thick place and coarse weft defects are attributed to yarn defects which are not only micro natured but are very crucial because they cause subtle variation in texture and hence in the light intensity of the acquired image.
b. **Twill Weave Normal and Defective Samples**

Figure 3.8 shows the images of twill grey fabric with different defects that have occurred during weaving. It is seen here that the twill weaving imparted diagonal pattern orientation for the fabric. The stitch defect is micro-natured, mostly localized and has orientation in horizontal direction whereas weft loose
defect has no orientation and is also localized to a small region besides being micro natured.

![Figure 3.8.1: Twill Weave Sample Images of S1 Class](image)

Figure 3.8.1: Twill Weave Sample Images of S1 Class  
a: Normal  b: Loose-weft  c: Stitch

As is seen in Figure 3.8.2 loose-weft defect is varying in its intensity (Refer Figure b and c). The images in the data base so created were subjected to defect detection using MA and CA and were also used during further experimentation. The details of which are given in the next section.

![Figure 3.8.2: Twill Weave Sample Images of S2 Class](image)

Figure 3.8.2: Twill Weave Sample Images of S2 Class  
a:Normal  b:Loose-weft-1  c:Loose-weft-2

### 3.4 GFDD using Morphological and Correlation Approach:

The initial experimental work was carried out to understand the response to the fabric texture in normal and defect region to the already tested algorithms. These included MA and CA. The experimental work includes discrete solution of fabric defect identification using off-line solution of applying MA and CA. This
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research work is carried out in MATLAB R2007a design and development environment using Image Processing (IP) and Neural Network toolbox.

The work on fabric defect detection as outlined in the flow chart of Figure 3.2 was formally was divided into two broad categories and hybridization of the first two viz.,

1. Spatial domain morphological approach which included “understanding morphological principle” and understanding various basics needed to design “structuring element”.
2. Frequency domain correlation approach which included “understanding response of correlation to texture” and “design needs of templates for finding defect region i.e. Region of Interest (ROI)”.
3. Hybrid Approach which included the understanding of response of texture to a hybrid of correlation and morphological approach.

The various image preprocessing steps consist of conversion of RGB image to gray image, elimination of noise enhancement of the fabric image etc. Various basic Morphological Operations (MO) of morphological approach include area opening, noise elimination, erosion, dilation etc. Selection of suitable template, implementation of correlation using FFT, application of suitable thresholding method for detecting appropriate defect region in fabric image are the various steps involved in correlation approach. The outcomes of this work helped us to formulate the design considerations required to be taken into account while designing and implementing MA based and CA based defect detection. Besides it also helped us to develop a hybrid approach containing both MA and CA.

3.4.1 Spatial Domain Morphological Approach (MA)

As described in Chapter 2, the basic idea of mathematical morphology to detect defect region of fabric image using the structuring elements of certain shapes is to obtain the original image information which thereby realizes image
analysis and identification. The relation between various parts of the image can be obtained by spanning the entire the image using structural elements, which helps one to extract useful information for structural analysis and description. Out of the two kinds of morphological operations viz., binary and gray scale morphological operations, a simple approach using binary morphological operations was adopted. Besides simplicity of implementation, this approach provides the privilege of reduced time of computation resulting into quicker guidelines for GFDD.

The basic operations like dilation, erosion, image closing and image opening operations etc. follow the well established equations for MA as stated in Chapter 2. This experiment was performed to study the effect of morphological operations (refer Section 2.3.2.d) on the fabric texture with subtle defects in plain and twill grey fabrics and confirm the use of erosion operation for removing the irrelevant details such as protrusion due to yarn in the fabric binary image and hence detecting ROI.

The literature review on MA for fabric defect detection [9, 24, 25, 26, 27] indicates that, the approach has been widely used for detection of twill and rarely on plain weave defects. Secondly, the reported fabric defect detection efficiency is mostly subjective and with False Alarm Rate (FAR) of 14% especially for normal samples. The studies further reveal the need for improvement in terms of achieving quantitative results, improving Overall Detection Accuracy (ODA) % and strengthening the robustness of the algorithm. More importantly subtle twill fabric defects need to be addressed. This indicates a need for further improvement in defect detection using MA. Additional relevant theory on morphological operations for MA is presented further.

**Background:**

**Blob Analysis:** It deals with the purpose of finding the statistics of ROI, such as area, minimum length and maximum length etc of ROI. Some morphological operations which assist the blob analysis are given below.
**Boundary Extraction**: Object boundary denoted by $\beta(A)$ can be obtained by difference of original object, $A$ from its dilated version. It can be obtained first by eroding image, $A$ by structuring element, $B$ and then performing the set difference between $A$ and its erosion given by,

$$
\beta(A) = A - (A \ominus B)
$$

(3.13)

**Region filling**: It is another important MO the objective is to fill the region inside a boundary. It is based on a set of dilations involving complementation and intersection. The filling operation is established using 4/8-connected background neighbors for 2-D/3-D morphological operations. Adopting the convention of '0' for non background points and '1' for the beginning point, $p$ inside the boundary of ROI, the region filling is expressed as,

$$
X_k = (X_{k-1} \ominus B) \cap A^c, \text{ for } k = 1, 2, 3, \ldots
$$

(3.14)

where, $X_0 = p$ (seed point) and $B$ is the structuring element. The algorithm is iterated till convergence is achieved. The set union of $X_k$ and $A$ contains the filled set and its boundary limits the result inside the region of interest.

**Extraction of connected component**: Extraction of boundary of image objects is another important morphological operation for automated image analysis which can be used for filling of ROI (Image filling). If $Y$ represents the connected component contained in a set $A$ and if seed point, $p$ of $Y$ is known then the following expression yields all the connected components of $Y$.

$$
X_k = (X_{k-1} \ominus B) \cap A, \text{ for } k = 1, 2, 3, \ldots
$$

(3.15)

Where, $X_0$ and $B$ have the same meaning as above. All the elements sought are labeled as 1. This helps in finding area of ROI.

### 3.4.1.1 Implementation of Morphological Approach

The experimentation using MA was carried out on samples of grey twill and plain weave separately. The grey fabric samples of microstructure defects such as loose-weft and stitch of twill weave whereas warp break, double pick and thick place defects of plain weave pattern were subjected to morphological
operations. The built-in morphological operations related instructions such as `bwareaopen`, `imclose`, `imfill`, `imerode` and `imdilate` and the built-in structuring elements of IP toolbox of MATLAB were used for the experimentation. The various steps followed for this approach on both weaving patterns are as shown in Figure 3.9.

The resolution of (1280 x 1040) pixels of the original image was reduced to (512 x 512) pixels using Microsoft Digital image editor. The purpose behind this was to make the image size handy and compatible with the need of FFT operation. After converting fabric RGB image to gray image, it was then subjected to the adaptive histogram equalization for contrast adjustment and subsequently to Ostu’s binarization [87]. This was then followed by morphological operations for noise removal and for location of defects by selecting an appropriate type and size of structural element typical of shape and size of one repeat element of normal weave pattern of fabric. Trial and error method is followed for the selection of shape and size of
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Structural element. Boundary of the defect was determined using connected component principle algorithm. The performance of all experimented GFDD algorithms were measured using Defect Search Algorithm (DSA). For this a true ‘0’ logic was assigned for defect sample if Region of Interest (ROI) i.e., defect area measured was beyond the range specified by the relation, $0.8 \times \text{RE} < \text{ROI} < 1.25 \times \text{RE}$, as per textile standard and RE is repeat element specific to a pattern otherwise a true logic ‘1’ was assigned indicating a normal sample. Performance metrics like ODA and FAR were used.

Morphological approach was carried out on twill and on plain weave pattern fabric defects.

A. Twill Weave Defect Detection

The gray images of twill fabric samples normal (N) with stitch defects (ST-F) (class S₁) and loose-weft defect (LW-F) (class S₂) are as shown in Figure 3.10.

![Figure 3.10: Twill Fabric Sample Gray Images](image)
a: Normal (N)  b: S₁-Stitch (ST-F)  c: S₂- Loose-weft(LW-F)

It is seen from the variation in intensity of these images that the defect varies in size and shape and they may appear at single place or at multiple places during weaving. Loose-weft defect is characterized by more protruding yarns than stitch type defect.
a. Experimental Results and Discussion

The Results of the processed images as per the flow chart of Figure 3.10 are as shown in columns $C_1$, $C_2$ and $C_3$ of Figure 3.11. Images of row $R_1$ correspond to the black and white images obtained after subjecting the images in Figure 3.8.1 to RGB to gray conversion(Figure 3.10) and then to Ostu’s thresholding that chooses the threshold to minimize the intra-class variance of the black and white pixels.

![Figure 3.11: Result Images Obtained after Sequence of Morphological Operations Applied on Twill Grey Fabric Samples Depicted along Column](image-url)
Table 3.3: Sequence of Morphological Operations Followed for Images in Figure 3.11

<table>
<thead>
<tr>
<th>Row Column</th>
<th>C₁: Normal (S₁ class)</th>
<th>C₂: Stitch Defect (S₁ class)</th>
<th>C₃: Looseweft Defect (S₂ class)</th>
</tr>
</thead>
<tbody>
<tr>
<td>R₁</td>
<td>Image area opened after thresholding adaptive histogram equalized gray level sample image in Figure 3.10</td>
<td></td>
<td></td>
</tr>
<tr>
<td>R₂</td>
<td>Closing of images in row R₁</td>
<td></td>
<td></td>
</tr>
<tr>
<td>R₃</td>
<td>Filling (small holes) of images in row R₂</td>
<td></td>
<td></td>
</tr>
<tr>
<td>R₄</td>
<td>Erosion of image in row R₃ with SE eye</td>
<td></td>
<td></td>
</tr>
<tr>
<td>R₅</td>
<td>Dilation of image in row R₅ with SE eye</td>
<td></td>
<td></td>
</tr>
<tr>
<td>R₆</td>
<td>Erosion of image with rectangle SE</td>
<td></td>
<td></td>
</tr>
<tr>
<td>R₇</td>
<td>Dilation of image in R₇ with rectangle SE</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The images in row R₁ were obtained after opening operation by properly choosing a suitable area obtained after many trials for retaining the seed of the pattern. Images after closing operation are depicted in row R₂. The defective grey fabric consists of protruding yarn resulting in the form of small pepper noise which needs (which gets exaggerated in fault region) to be removed by filling operation. The images filled after closing operation are depicted in Row R₃. The next step of extraction of ROI i.e. defective region, was carried out by two successive sets of morphological operations consisting of erosion and dilation using structuring element 'eye' for first set of operation and rectangular structuring element for the second set of operation. Size of rectangular structuring element was obtained by many trials and observations of the results produced. The sequence of morphological operations followed is shown in Table 3.3. The results of these operations are depicted in rows R₄, R₅, R₆, and R₇ respectively in Figure 3.11. For this study, two separate morphological operations algorithms were developed viz., Algorithm for Normal Without imfill (ANWOIMF) and Algorithm for Fault With Imfill (AFWIMF) operation. The number of trials taken by setting various values for different parameters for morphological operations for GFDD of twill fabric samples using DSA and the corresponding results are as depicted in Table 3.4.

Defect search algorithm is a simple binary search algorithm used to find the presence or absence of defect in a given sample indicating sample as defective or defect free. For sample DSA results refer Table IV.A and IV.B of
APPENDIX-IV. From the rigorous experimentation for selecting structuring element, it was found that, three factors viz., size and type of the structuring element and the extent of noise removal play a major role in the success rate of defect identification. Disk type structuring element helps in the removal of noise due to protruding yarns since it approximately resembles the shape of twill weave pattern primitive.

Table 3.4: Trial Test Results of Morphological Operations on $S_2$ Class Normal (N) and Loose-weft(LW-F) for Different Test Set Parameters with Binary Image Opening using 60 Pixels.

<table>
<thead>
<tr>
<th>Sr. No</th>
<th>Algorithm</th>
<th>SE used/Noise Removal</th>
<th>SE used for MO</th>
<th>Size of Rectangle SE</th>
<th>Number of Samples Detected correctly</th>
<th>Accuracy of correct Detection (ODA)%</th>
<th>%FAR</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Yes/No</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>S$_2$-Normal, SE for noise removal –DISK 0, Total samples Tested 115</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>ANWOIMF</td>
<td>No</td>
<td>Eye 9</td>
<td>28,17</td>
<td>106</td>
<td>94.0</td>
<td>7</td>
</tr>
<tr>
<td>2</td>
<td>ANWOIMF</td>
<td>No</td>
<td>Eye 9</td>
<td>28,15</td>
<td>38</td>
<td>34.0</td>
<td>66</td>
</tr>
<tr>
<td>3</td>
<td>AFWIMF</td>
<td>Yes</td>
<td>Eye 7</td>
<td>28,17</td>
<td>73</td>
<td>64.0</td>
<td>36</td>
</tr>
<tr>
<td>4</td>
<td>ANWOIMF</td>
<td>No</td>
<td>Eye 7</td>
<td>28,20</td>
<td>112</td>
<td>97.4</td>
<td>2.6</td>
</tr>
<tr>
<td>5</td>
<td>ANWIMF</td>
<td>Yes</td>
<td>Eye 7</td>
<td>28,20</td>
<td>96</td>
<td>83.5</td>
<td>16.5</td>
</tr>
<tr>
<td>6</td>
<td>ANWOIMF</td>
<td>No</td>
<td>Eye 7</td>
<td>28,17</td>
<td>90</td>
<td>79.0</td>
<td>21</td>
</tr>
<tr>
<td>S$_2$-Looseweft Faulty, SE for noise removal –DISK 0, Total samples Tested 75</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>ANWOIMF</td>
<td>No</td>
<td>Eye 7</td>
<td>28,17</td>
<td>55</td>
<td>76.6</td>
<td>14.4</td>
</tr>
<tr>
<td>2</td>
<td>AFWIMF</td>
<td>Yes</td>
<td>Eye 7</td>
<td>28,17</td>
<td>71</td>
<td>94.7</td>
<td>5.4</td>
</tr>
<tr>
<td>3</td>
<td>ANWOIMF</td>
<td>No</td>
<td>Eye 7</td>
<td>28,20</td>
<td>66</td>
<td>88.0</td>
<td>12</td>
</tr>
<tr>
<td>4</td>
<td>AFWIMF</td>
<td>Yes</td>
<td>Eye 7</td>
<td>28,20</td>
<td>73</td>
<td>97.3</td>
<td>2.7</td>
</tr>
<tr>
<td>5</td>
<td>AFWIMF</td>
<td>No</td>
<td>Eye 9</td>
<td>28,17</td>
<td>42</td>
<td>56.6</td>
<td>43.44</td>
</tr>
</tbody>
</table>

The performance measures like ODA and FAR are used. It is seen from the Table 3.4 that,

- For normal samples, higher ODA is obtained by morphological operation on without imfill operation whereas for LW-F samples higher ODA is obtained by MO operation with imfill operation.
- While testing the normal/loose-weft defect samples for fabric class $S_2$, opening operation using 60 pixels, structuring element viz., eye of size 7 for one stage of morphological operations and rectangle structuring element with size parameters 28, 20 for another stage of morphological operations gave ODA results of 97.4% (Refer sr. no 4 for LW-F)/97.3% (Refer sr. no 3 for N) respectively.
• Noise removal in faulty sample result into better ODA in contrast to same in normal sample. This can be attributed to the fact that normal sample does not have protruding yarn leading to absence of noise in normal fabric image. So its removal leads to deterioration of % ODA.

• Overall detection accuracy decreases as the size of structuring element is reduced. This is due to the fact that, if the size of structuring element chosen is smaller than the size of one repeat element of the fabric pattern in pixels, then subsequent morphological operations using this structuring element fails to filter the ROI, thus leading to misdetection of ROI.

• Appropriateness of the selection of type of SE and size of structuring element used in different steps of morphological operations for defect region detection seem to be correct. The high ODA of the order of 97% obviously reflects the correctness of choice of SE and size of structuring element for both normal and faulty samples with IMFILL operation being absent in procedure of detection as normal.

• The ODA for normal without imfill and that for defective samples with imfill operation is 97.4 and 97.3% respectively. This is due to the fact that noise due to the protruding yarns is absent in normal image and thus does not need imfill operation. So this step when used will cause the removal of unnecessary information leading to higher FAR. This further suggests a two pass MA algorithm for GFDD.

In summary normal twill fabric does not need noise removal whereas; it is an essential step of MA for defective samples. This is attributed to the fact that there is noise addition due to protruding yarn in the normal region during weaving. Accordingly MA algorithm needs modification to achieve optimized ODA for both normal and defective samples. The above observations suggest an introduction of a two pass MA algorithm as shown in Figure 3.12 for segregating normal and defective samples using MA which is self explanatory.
Figure 3.12: Modified Flow Chart of Morphological Approach

B Plain Weave Defect Detection

The experimental procedure similar to MA of twill grey fabric as shown in the flow chart of Figure 3.9 was followed on few benchmarking plain weave fabric defect samples viz. warp-break, thick place and double pick. Two sets of observations were taken on the fabric images. The first set consisted of all MO steps with image filling operation and while the second set consisted all steps except image filling operation on the histogram equalized image in Row R₁ of Figure 3.13.a and 3.13.b respectively. The sequence of MOs followed is shown in Table 3.5. The results of MA approach are discussed in the following section.
a. Experimental Results and Discussion

Following observations are made for the MA application for normal and defective plain grey fabric samples:

- Observing Figure 3.13.a for warp break and thick place defect, it is clear that, MA operation with IMFILL operation fails to detect ROI for plain weave pattern. This is due to the fact that, plain shirting fabric being
made out of very fine yarn count makes the repeat unit of weave pattern very small in area and very dense in texture nature. This makes the image filling operation to remove information more than expected causing too high degradation of ROI (Refer row images from $R_5$ to $R_7$ of Figure 3.13.a). Referring to Figure 3.13.b it is seen that, though elimination of IMFILL operation from MO sequence results in improvement in detection of ROI but still it does not give satisfactory results in detection of ROI (Refer row $R_8$ of Figure 3.13 b).

- Comparing images in row $R_8$ for the warp break, thick-place and double pick in Figure 3.13.b, it is seen that detection of ROI for warp break is better than that for double pick while it is the worst for thick-place samples.

Table 3.5: Sequence of Morphological Operations Followed for Images in Figure 3.13

<table>
<thead>
<tr>
<th>Row/Column</th>
<th>C₁: warp break (S₁ class)</th>
<th>C₂: Thick place (S₂ class)</th>
<th>C₃: Double pick Defect (S₃ class.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fig a</td>
<td>Fig. b</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$R_1$</td>
<td>$R_1$</td>
<td>Thresholded Gray images</td>
<td></td>
</tr>
<tr>
<td>$R_2$</td>
<td>$R_2$</td>
<td>Image area opened after thresholding</td>
<td></td>
</tr>
<tr>
<td>$R_3$</td>
<td>$R_3$</td>
<td>Closing of images of row $R_2$</td>
<td></td>
</tr>
<tr>
<td>$R_4$</td>
<td>-</td>
<td>Filling (small holes) of images of row $R_3$</td>
<td></td>
</tr>
<tr>
<td>$R_5$</td>
<td>$R_4$</td>
<td>Erosion of images of row $R_4$ (R₄) with SE eye</td>
<td></td>
</tr>
<tr>
<td>$R_6$</td>
<td>$R_5$</td>
<td>Dilation of images of row $R_5$ (R₅) with SE eye</td>
<td></td>
</tr>
<tr>
<td>$R_7$</td>
<td>$R_6$</td>
<td>Erosion of images of row $R_6$ (R₆) with rectangle SE</td>
<td></td>
</tr>
<tr>
<td>$R_8$</td>
<td>$R_7$</td>
<td>Dilation of images of row $R_7$ (R₇) with rectangle SE</td>
<td></td>
</tr>
<tr>
<td>$R_9$</td>
<td>$R_8$</td>
<td>ROI detection for image of row $R_8$ (R₈)</td>
<td></td>
</tr>
</tbody>
</table>

Note: $R_{n}/R_{n-1}$ – A particular MO on image of row $R_n$ with imfill and $R_{n-1}$ without imfill

The above observations of MA on plain weave defects suggest that, Morphological Operations operation fails very badly for plain weave defects in detection of normal region and ROI. Image filling operation does not work effectively for noise removal for normal as well as for detection of defect. This is attributed to the fact that the noise addition due to protruding yarn for defective region of fine count plain weave fabric is almost feeble even in the defect region. Accordingly the steps of MA need modification to achieve better results for
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detection of ROI and hence to achieve good ODA for both normal and defective samples.

3.4.1.2 Observation and Comments

The experiment confirms the usefulness of morphological approach applied on grey twill weave fabric pattern for detection of stitch and loose-weft defect present in a single image or similar multiple defects located at different locations of the fabric image. It is seen that the MA greatly helps in detecting the grey twill fabric defects but can not perform well for detection of plain weave defects. The method was found to be quite simple and fast. But as the optimal size of SE to locate and detect exact area of fault was obtained after many trials, it needs further interrogation for automatic selection of size of SE. Further this method failed to effectively detect the faults in plain weave grey fabric. Also for the twill fabric, the set of parameters for MA are not unique for both normal and defective samples. The parameters set for defective sample identification resulted into wrongly identifying normal samples as defective ones. These two issues indicate further investigation in MA approach for GFDD.

Finally, it can be concluded that, the MA algorithm can be a better solution for detection of fabric defects with some modification so as to eliminate observed discrepancy. However it has one major drawback of first finding the seed of the defect and then the actual defect area. This requires finding a way to design structuring element and to make the MA operation independent by automatic selection of size of SE. These results and their analysis encouraged us to explore MA further on the basis of the Fourier transform approach recommended by Mallik-Goswami and Datta [20] where they have applied MA on aperiodic image after removing periodic information by Fourier transform. As against this, we felt that, periodic information can act as a basis for selection of structuring element. In Chapter-4 results of the experimentation based on this notion are presented.
The objective of the next sub-experiment was to compare the suitability of correlation approach by template matching method for GFDD. Both plain and twill weave fabric samples were considered for this experimentation.

3.4.2 Frequency Domain Correlation Approach (CA)

3.4.2.1 Introduction

Basis for selection of correlation approach for GFDD research is the verification and confirmation of the research carried out by Bodnarova et al. [33, 34 and 35] for FDD. They have used the correlation coefficient from multiple templates to generate a correlation map for fabric defect declaration and have achieved correlation sensitivity of 95% for 15 defective fabric images with five different defects. They showed that correlation approach appears to have sufficient sensitivity, specificity and potential for real-time implementation indicating further efforts in algorithm development. They also have reported that these algorithms still require rigorous testing against multiple flaw types on multiple backgrounds.

From the literature survey, it is seen that the method of correlation has been used extensively especially for pattern matching. However the application of this method to detect microstructure defects and multiple grey fabric faults seem to be rarely addressed and suggests its rigorous testing against multiple flaw types [33, 34 and 35]. Also it is known fact that, correlation is capable of concentrating to smaller local feature variations \(B_8\). This kind of phenomenon is observed in fabric defects of micro-nature and also localized in nature. These can occur due to loss of regularity and change in the intensity levels in the faulty region of the image. Thus we were motivated to use correlation as a tool to detect microstructure defects in grey fabrics.

3.4.2.2 Background

Given an image \(f(x, y)\), the correlation problem is to find all places in the image similar to the given sub image or template \(h(x, y)\). The 2-D
spatial correlation is analogous to convolution theorem and is as given below.

\[ f(x, y) \ast h(x, y) \Leftrightarrow F^*(u, v)H(u, v) \]  

(3.16)

Thus spatial correlation can be obtained as the inverse of product of conjugate of Fourier transform times the transform of the other [32]. Equation (3.16) can be rewritten as,

\[ f(x, y) \ast h(x, y) \Leftrightarrow \frac{1}{MN} \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} f^*(x, y)h(x + m, y + n) \]  

(3.17)

Here + sign indicates that, \( h \) is not mirrored about the origin. \( M \) and \( N \) are the image width and length in pixels and \( m \) and \( n \) are the spatial shift of the template with respect to image coordinates \((x, y)\). This basic correlation relation is extended to more intuitive image and sub image for matching where it considers finding matches between sub image \( w(x, y) \) of size \( J \times K \) within an image \( f(x, y) \) of size \( M \times N \) where \( J \leq M \) and \( K \leq N \). In its simplest form, the correlation between \( f(x, y) \) and \( w(x, y) \) which is commonly used in practice is given by,

\[ c(x, y) = \sum_s \sum_t f(s,t)w(x+s,y+t) \]  

(3.18)

for \( x = 0, 1, 2, \ldots, M - 1, y = 0, 1, 2, \ldots, N - 1 \) and summation is taken over the region where \( w \) and \( f \) overlap and \( c(x, y) \) is correlation coefficient. The maximum value(s) of \( c \) indicate the position(s) where \( w \) best matches \( f \), then that region of image \( f(x, y) \) with the maximum values of correlation coefficients is said to be highly correlated with \( w(x, y) \).

### 3.4.2.3 Implementation of CA

Grey fabric with plain and twill weave pattern having different defects as listed in Table 3.6 were considered for defect detection using the correlation approach. The plain weave fabric defects such as missing warp, multiple defects, double pick, thin place, loose-weft and twill fabric pattern defects such as stitch, bump mark and weft loosing of were chosen for study.
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Table 3.6: Fabric types/ Defect Types for CA

<table>
<thead>
<tr>
<th>Sr. No</th>
<th>Plain Weave Defect type</th>
<th>Sr. No</th>
<th>Twill Weave Defect type</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Warp break (S₁)</td>
<td>1</td>
<td>Stitch(S₁)</td>
</tr>
<tr>
<td>2</td>
<td>Double pick(S₂)</td>
<td>2</td>
<td>Loose-weft(S₂)</td>
</tr>
<tr>
<td>3</td>
<td>Thick Place(S₃)</td>
<td>3</td>
<td>Bump mark(S₂)</td>
</tr>
<tr>
<td>4</td>
<td>Loose-weft(S₂)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>Multiple break Defect(S₁)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

a. Image Preprocessing

The procedure as mentioned in the flow chart of Figure 3.14 was adopted on defect free and fabric fault images. The results of CA are divided into two classes depending on fabric pattern viz., plain weave fabric defects and twill weave fabric defects and are presented further. In all the cases correlation analysis, the defect regions are indicated by the bright region.

Reading the RGB Image

- Converting of RGB to Gray image
- Adjusting intensity of image adaptively

Extracting the defective area for use as a template

Computing correlation based on FFT of original image with template image

Computing of maximum, minimum & Average value of correlation coefficients

Thresholding of correlated image using statistics of Correlation coefficients

Calculating defect area using Blob analysis
Displaying ROI of image

End

Figure 3.14: Flow Chart for Correlation Approach (CA)
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The RGB colour image was converted to gray image for further processing and then was subjected to adaptive histogram equalization for contrast adjustment. It was then operated by an intelligently selected correlation defect template of appropriate size to identify the maximum correlated region.

b. Algorithm for Correlation Approach

In CA algorithm for achieving defect detection, the correlation of the template image with the original image was computed by rotating the template image by 180° and then using the FFT-based convolution technique described by fast convolution. This is for the reason that, if the convolution kernel is rotated by 180°, then the convolution is equivalent to correlation. To make the CA more efficient than its implementation in spatial domain, the size of kernel was made equal to the size of the image. Correlation Coefficients (CC) were then thresholded using the simple statistics of the coefficients such as mean and maximum value to display the defect region. To match the template to the image, instructions of MATLAB V 7.4 like fft2 and ifft2 were used. The images of chosen samples were processed as per the flow of the above steps. The results of this processing on plain and twill weave are presented in the following section.

3.4.2.4 Experimental Results

Correlation experimentation was carried out in two parts. The first part of the experimentation was focused on plain weave fabric defects and twill weave defects as per Table 3.6 were considered for the second part of CA approach.

A. Plain Weave Defects and Results

With reference to Figure 3.15 Column C₁ depicts images of warp break, double pick, thick-place and loose-weft defects respectively from top to bottom. The defect templates corresponding to these defects are as shown in column C₂ while the result of correlation convolution of the defect images with their respective defect template are shown in column C₃. The thresholded defect area
for each kind of defect obtained after thresholding of correlation coefficients are as shown in $C_4$ column of Figure 3.15.

![Figure 3.15: Application of Correlation Approach on Plain Weave Pattern Defects](image)

<table>
<thead>
<tr>
<th>Defect name Row wise</th>
<th>IP operation Column wise</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R_1$: Broken warp</td>
<td>$C_1$: Gray Image</td>
</tr>
<tr>
<td>$R_2$: Double pick</td>
<td>$C_2$: Defect Template</td>
</tr>
<tr>
<td>$R_3$: Thick place</td>
<td>$C_3$: Correlation Result</td>
</tr>
<tr>
<td>$R_4$: Loose-weft</td>
<td>$C_4$: Result of Thresholding image in column $C_3$</td>
</tr>
</tbody>
</table>

Table 3.7 shows the details of results of CA applied on various plain weave defects. The threshold was fixed for the experimentation by trial and error method and observing for the expected defect area manually. The threshold which best approximates the actual defect location and area was chosen for further experimentation on other samples of the similar kind. Also it is been found that, the defect area identified was dependent on the size of the defect template.
However the multiple break fault shown in Figure 3.16.a needed an intelligent choice of a template. Multiple break defect consisting of warp breakage and weft wise defect as in Fig 3.16.a was detected (as shown in Figure 3.16.h) using the logical OR operation of correlation results of two independent appropriate templates shown in Figure 3.16.b and e to detect two different kinds of defects existing along warp and weft direction respectively.

To summarize CA on plain weave GFDD, five different kinds of plain weave defects including defects of subtle nature were considered. Observing the various results of CA in Figure 3.15 and 3.16.d, h, it is seen that, the results are not very satisfactory, since part of the Normal Region also is Identified as Defective (NRID) (Refer NRID in row R_3, R_4 of Figure 3.15 and 3.16.g, h corresponding to column C_4 in each Figure) in majority of these cases. Also there is a need of different kind of template for each kind of defect considered which makes GFDD a tedious and time consuming process. To check the suitability of CA for GFDD on different types fabric the above experiment was repeated on twill grey fabrics, the results of which are given in below section.
B. Twill Weave Defects and Results

Twill weave pattern used for suiting is characterized by the diagonal pattern. In plain weave, the defects are mostly seen to be extended along warp wise (lengthwise) and weft-wise (widthwise) direction. But in twill weave, additional localized defects like stitch and loose-weft are produced along with weft direction defect like bump-mark. Details of the experimentation on twill weave defects and the results on these are presented below. Localized stitch defect, loose-weft defect at multiple places and warp-wise bump mark defect as depicted in column C₁ of Figure 3.17 were identified by convolving the original gray images in C₁ with their corresponding defect templates shown in column C₂.

![Figure 3.17: Application of Correlation Approach on Twill Weave Pattern Defects](image)

<table>
<thead>
<tr>
<th>Defect name</th>
<th>Row wise</th>
<th>IP operation Column wise</th>
<th>Result details</th>
</tr>
</thead>
<tbody>
<tr>
<td>R₁: S₂-Stitch</td>
<td>C₁:Gray Image</td>
<td>C₂:Defect Template</td>
<td>C₄:Result of Thresholding image in column C₁</td>
</tr>
<tr>
<td>R₂: S₃-Looseweft</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R₃:Bumpmark</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
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It was found that the twill fabric defects are identified approximately as seen in column $C_4$ after thresholding correlation image in $C_3$ of Figure 3.17. However it was also observed that even some normal fabric region is falsely identified as defective at several places (Refer NIRD region in Figure 3.17). Thus subtle micro defects of twill weave fabric can be detected using CA approach with modification to reduce NRID. Also this approach requires independent template depending on the kind of defect under consideration.

3.4.2.5 Observations and Comments

The detailed application of correlation using template matching was carried out on different kinds of fabric defects of plain and twill weave fabric patterns consisting of single and multiple defects in a single image as well as similar multiple defects located at different locations of the image. It is seen that the correlation analysis greatly helps in detecting the grey fabric faults of both types. But the exact area of fault indicated by this method depends on how best the defect template for a given type of fault is chosen and also on the threshold value.

The method was found to be quite simple and fast. Also it is observed that template matching using correlation technique helps in detecting the faults of different types from simple to complex nature and of different sizes for all real fabric images of different weave patterns. Though correlation technique can detect variety of defects, its dependency on the right defect template, template size, thresholding and false detection of normal region as defective, puts limitation on its use. All these are indicative of further exploration on CA for GFDD. The other disadvantage is that fabric without defect is detected as defective which is objectionable. This issue demands further research work in this area. Therefore to overcome these, a Hybrid of CA followed MA is experimented and the details of the same are presented in the next section.
3.5 Hybrid Approach(HA) using CA and MA(Our contribution)

From careful observation of the results on FDD on plain weave and twill weave, it seen that both MA and CA independently can identify the defect region i.e. ROI, but some times the normal region of the fabric also gets identified as the defective. To overcome this drawback and to utilize the advantages of correlation property of CA and filtering property of MA to detect ROI for GFDD, the next drive in this research was a hybrid approach. In this direction hybrid algorithm using combination of CA and MA was developed and experimental results were carried out. The results of this hybrid approach on fabric defects using the suggested hybrid method are presented below.

a. Hybrid GFDD Algorithm

The flow chart for HA is as shown in Figure 3.18 which is self explanatory.

- Reading the image and Conversion of RGB to gray
- Adaptive histogram equalization for contrast adjustment

- Conversion to binary image
- Noise removal due to protruding yarn

- Extracting the defective area for use as a template
- Computing correlation based on FFT of original image with template image

- Computing of Maximum, Minimum & Average value of correlation coefficients
- Thresholding of correlated image

- Selection of appropriate SE
- Application of MO on image
- Two step erosion and dilation

Displaying the thresholded image

Figure 3.18: Flow Chart for Hybrid Approach
In hybrid processing, after preprocessing of the fabric image, each image was subjected to correlation approach first using a defect dependent template for each kind of defect as was suggested and used in Section 3.4.2. Further all morphological operations as explained in Section 3.4.1 were applied after thresholding the correlation coefficients. The implementation results of this Hybrid Approach (HA) are discussed in the following subsection.

### b. Experimentation Results

The plain weave defects such as double pick, warp-break, thick-place and twill weave defects viz. loose-weft were considered for this study. The results of HA on these defects are shown in the rows $R_1$, $R_2$, $R_3$, $R_4$ and $R_5$ respectively of Figure 3.19. The columns of $C_1$, $C_2$, $C_3$ and $C_4$ of Figure 3.19 depict the defect gray image, results of CA, MA and the hybrid CA and MA approach respectively. Table 3.9 gives the defect type shown row wise in image 3.18 and algorithm to which each defect is subjected. Focusing the discussion to row $R_3$ of Figure 3.19 on plain weave double thick place defect, it is seen from images in column $C_2$ and $C_3$ that, neither MA nor CA can independently identify the defective region correctly. This is for the reasons as mentioned earlier that MA cannot catch purely ROI for plain weave defects when count of the fabric becomes fine. Also in CA as stated earlier, defect area identification is mainly dependent on the thresholding value of correlation coefficients. This threshold value plays a very crucial role in identification of ROI. Choice of good threshold is a difficult task. So there is a chance that defect free region could be detected as defect region This is quite evident from images in column $C_3$ and $C_4$ that, the problem of identifying the normal region as defective at several places is almost eliminated by the successive CA followed by MA as seen from the result images in column $C_4$. Similar results were observed for the other kind of defects of plain weave and twill weave as depicted in Figure 3.19.
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Figure 3.19: Results of MA, CA and Hybrid (CA+MA) Approach Applied on Plain Weave Defects (Row-R1, R2, R3, R4, R5) and Twill Weave Defect (Row-R6)

Table 3.9: Details of MA, CA and HA Applied on Plain and Twill Weave Defects

<table>
<thead>
<tr>
<th>Weave Type</th>
<th>IP operation (Column wise)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Plain</td>
<td></td>
</tr>
<tr>
<td>R1: S2-Double pick</td>
<td>C1: Gray Image</td>
</tr>
<tr>
<td>R2: S2-Warp break</td>
<td>C2: Result of MA</td>
</tr>
<tr>
<td>R3: S2-Thick place</td>
<td>C3: Result of CA</td>
</tr>
<tr>
<td>R4: S2-Loosewft</td>
<td>C4: Result of HA</td>
</tr>
<tr>
<td>R5: S2-Double pick</td>
<td></td>
</tr>
<tr>
<td>Twill</td>
<td></td>
</tr>
<tr>
<td>R6: S2-Loosewft</td>
<td></td>
</tr>
</tbody>
</table>

3.6 Summary

The basic objective of this experimentation phase was to establish the close link between the theory of morphology and correlation technique and their implementation results for fabric defect detection approach. By verifying the theory presented in published IEEE and Textile Research Journal papers, the various preprocessing methods and response of the texture to MA based and
correlation based object recognition techniques has been confirmed. The analysis of the above experimental work brings about the following important design considerations of fabric defect detection scheme;

1. MA and Correlation approaches for GFDD confirm the theory of object identification of interest in a fabric image.

2. In morphological based GFDD, it is necessary that the size and type of structuring element has to be correctly chosen such that, it is based on the shape and probable size of one pattern element.

3. Size of structuring element for different stages of MA operation needs to be selected by many trials. So there is a need for establishing some relation of selection of structuring element size with pattern.

4. Results of MA for GFDD of twill are better than of those on plain weave FDD in finding ROI. So it suggests for further exploration on MA on plain weave GFDD.

5. It is essential to verify whether the MA algorithm really leads towards the detection of the defect at the correct location or not. It can be done by or by plotting simple gray level sum plots in x and y direction of the image.

6. Correlation approach using template matching can identify defects in different kind of fabric of plain and twill weave patterns consisting of single and multiple defects in a single image as well as similar multiple defects located at different locations of the image.

7. The exact area of fault indicated by this method depends on how best the template for a given type of fault is chosen and also on the threshold value.

8. Though correlation technique can detect variety of defects, its dependency on the right template, template size and thresholding puts limitation on its use. This indicates that the template chosen should be based on pattern and not on type of defect.

9. The hybrid approach of CA and MA combined has resolved the problem of only CA or MA misidentifying the normal region as defect region. Hence it
appears to be promising method for GFDD. Such hybrid method does not seem to have been reported in the literature so far. **Therefore we claim this as one of the initial contributions of our research work.**

10. The performance of hybrid approach of CA and MA is found to work well for both plain and twill weave pattern defects for identifying the defect region.

In the first experiment structure of structuring element for MA plays a key role in detection of defect region of interest. Two features of structuring element to be considered are its size and shape. So the design of structuring element that acts as a filter for MA needs to be explored further. Also this points out the need for automation for structuring element size selection. This seems to be the attractive base design solution for designing defect detection scheme in which the design aim is to determine the size of the structuring element based on algorithms that can detect periodicity of weaving pattern for weaved fabric defects. In the second experimentation using correlation, more striking and important observation is that the area of defect identified depends on the size of defect template. This can be attributed to the fact that the correlation coefficients are larger only for the region of the defect where it is more intense, also the thresholding plays a role to decide defect area. So there is need to further investigate the independency of templates to detect defect area and also to automatically select a thresholding of correlation coefficients obtained using template. Both MA and CA methods need modification.

In the third experiment of HA, better performance of hybrid approach of combining CA and MA combined is attributed to the fact that the benefits of CA and MA doubly take care of retaining only ROI i.e. only defect part due to the inherent property of CA, detecting template matched region (i.e. defect region due to use of defect dependent template) and MA aiding to filter any remaining repetitive fabric pattern after CA and also enhancing the defect region of interest with the help of appropriate SEs.
However all these experiments support only detection and not the defect classification. This suggests a need for further investigation to assist grading of the fabric (Refer Appendix-II). The information such as number of defects detected in a given area and the area occupied by the defect w.r.to standard grey fabric may be used for classification purpose. It is further recommended that a modified approach (combining MA and CA) should incorporate automatic selection of size of SE for MA while defect independent template for CA.

The study on fabric surface indicates that, the fabric texture is characterized by a 2-D regular global stationary texture imparting periodicity to the fabric texture. Most of the fabric defects disturb this periodicity. Spatial domain co-occurrence matrix though can determine periodicity but it is computationally heavy [43, 46]. Also autocorrelation function can work well for finding the periodicity [68] of only macro textures but not suitable for the anisotropic micro texture such as shirting and suiting fabric [Bt]. Fourier transform is a known global method and it has the basic property of detecting periodicity. This periodicity property of Fourier transform can assist selection of size of weaving pattern primitive and also defect independent normal template of width proportional one repeating element. Also this gives an intuition that, Fourier transform applied on the fabric image under study will have a disturbed distribution of frequency components due to presence of defects as compared to normal sample image. This suggests the usefulness of Fourier Transform algorithm for GFDD. Hence further research is based on using modified Fourier transform approach for detecting the fabric defects.

The details of the research work based Fourier transform approach to find the periodicity of pattern and performance evaluation of proposed extended approach of Fourier transform and modified MA and HA approach using extended approach of Fourier transform for GFDD is presented in Chapter 4. Modified FPS assisted feature extraction and classification using LMBP are presented in detail in Chapter 5.