

# Computer Vision based Defect Detection and Identification in Handloom Silk Fabrics

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## ABSTRACT

Fabric defect detection and classification plays an important role in inspection of fabric products. Many fabric defects are very small and undistinguishable, which can be detected only by monitoring the variation in the intensity. Currently, in almost all the fabric industries the process of defect detection is done manually using skilled labor. An automated defect detection and identification system would naturally enhance the product quality and result in improved productivity to meet both customer demands and also reduce the costs associated with off-quality.

The main objective of this proposed work is to check whether the fabric material is defective or not, if defective, then identify the location and type of the defect. This paper deals with the defect detection process using Multi Resolution Combined Statistical and Spatial Frequency (MRCSF), Markov Random Field Matrix method (MRFM), Gray Level Weighted Matrix (GLWM) and Gray Level Co-occurrence Matrix (GLCM).

## General Terms

Multi Resolution Combined Statistical and Spatial Frequency (MRCSF), Markov Random Field Matrix method (MRFM), Gray Level Weighted Matrix (GLWM) and Gray Level Co-occurrence Matrix (GLCM)

## Keywords

Defect Detection in Silk Fabrics, Pattern Recognition,

## 1. INTRODUCTION

One of the most important industries, which is dominating today's world is the textile industry, with almost numerous fascinating products being produced every minute to satisfy the needs of the customers. Fabrics of various kinds and many designs are very much attracted by people irrespective of caste, creed and nation. Fabric industry can be considered as an evergreen industry, where in there are no rises and falls which can be affected either by the global or national sense.

Fabrics, in olden days were hand-woven by making use of hand-twinned cotton. Even today, some delicate threads such as silks from silk worms are preferred to be hand-woven rather than machine-woven. Now-days, power-loom have dominated a lot on handloom, as a result of which the Government of India along with the respective State Governments gives subsidiaries to the weavers, co-operative societies handling handloom fabrics and in certain special cases, even the Sericulture Department.

Handlooms constitute a rich cultural heritage of India. The handloom weaving, as an economic activity, provides livelihood to many people. The element of art and craft present in Indian handlooms makes it a potential sector for the upper segments of market in domestic as well as global. The sector accounts for 13% of the total cloth produced in the country [1]. The strength of Handloom lies in introducing innovative design, which cannot be replicated by the power-loom. Innovative weavers with their skillful blending of myths, faiths, symbols and imagery provide their fabric an appealing dynamism. In spite of the Government intervention through financial assistance and implementation of various development and welfare schemes, the number of handlooms is continuously reducing in the country. The reasons are manifold. New generations are not readily joining the weaving activity, low wages, continuous increase in yarn prices, obsolete technologies, unorganized production system, low productivity, inadequate working capital, conventional product range, weak marketing link, overall stagnation of production and sales and, above all, competition from power-loom are the factors forcing the handloom sector difficult to survive.

Handloom industry in Tamil Nadu plays an important role and provides employment for more than 4.29 lakh weaver households and about 11.64 lakh weavers [1]. According to the Director of Handlooms & Textiles, Government of India, about 2.11 lakh handlooms are functioning in 1247 handloom weavers' co-operative societies and the remaining looms are outside the co-operative fold. The handloom weavers' co-operative societies mostly exist in Rural and Semi-Urban areas, where there is large concentration of handloom weavers.

## 2. QUALITY OF FABRICS

Generally, as any product in the market claims its quality, fabrics too have their own quality. The better the quality; on the customer perspective, the producer can expect more sales and on proprietor perspective, can fix a higher price. The manufacturer would always prefer to produce the highest quality goods within the shortest span of time. Till date, the process of identification, classification and correction of defects produced in a fabric; be it a handloom or machine weaved, is done manually. Humans are prone to errors; and more over the process involves a huge amount of caution during the process. A statistics proves that even the highest fabric inspector is capable of identifying only upto 70% of defects, whereas 30% remains unidentified, till it reaches the

end-user. All these factors lead to a growing need for an automated fabric defect detection system which is the main objective of this paper.

### 3. DEFECTS IN FABRICS

In order to identify the most detrimental defects in textile fabrics, an industry survey was conducted to identify the most frequently occurring defects and the most costly defects as far as points were concerned. Data from leading fabric manufacturers was collected for their typical defects. Broken picks, harness drops, and start marks top the list of the most frequently occurring defects. Broken ends, broken picks, waste and coarse picks were the most costly defects. A wide variety of defects are represented; many defects are a direct cause of loom malfunction while others are from faulty yarns.

A broader classification is presented in this paper based on the survey to various industries located in and around Salem. The defects appearing in a silk fabric can be classified as

1. Manufacturing or Weaving defects [2] and
2. Handling Defects

Both these are explained in detail with a special focus on silk fabrics.

#### 3.1 Manufacturing or Weaving defects

##### 3.1.1 Missing Ends (Chira):

A defect where one or more ends are missing in the fabric is called “Chira”, which is shown in the figure 1. It constitutes 10 – 50 percent of total defects in loom static cloth

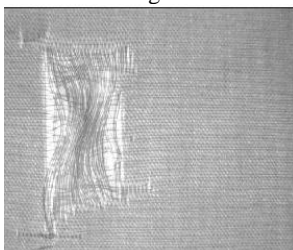


**Fig 1: Missing Ends (Chira)**

##### 3.1.2 Float (Jala) :

Jala is formed when there is no proper interlacement of the warp and weft yarns over a certain area, as shown in the figure 2.

**Causes:** Entanglement of adjoining ends in the regions between the heads and the fell of the cloth, knots with long tail ends, oozy and undersized warp, breakage of heald on running loom cause such entanglement



**Fig2: Float**

##### 3.1.3 Shuttle Smash

The defect is caused when many ends break consequent to a shuttle trap.

**Causes:** Wrong timing of shedding, soft picking, insufficient checking of shuttle in the boxes, unbalanced shuttle, entanglement in the warp, damaged or broken picking.

##### 3.1.4 Temple Marks

Yarns are distorted from their true paths and fine holes are caused near the sledge.

##### 3.1.5 Stains (Daghi)

Caused by lubricants, due to lack of care on the part of operatives and the poor oiling and cleaning practices. A sample of a stained cloth is shown in the figure 3.

##### 3.1.6 Hole in the cloth

The cloth with any defect reformed, this portion becomes a hole and will be a waste.

**Causes:** Warp of weft float, shuttle smash, sharp edge on cloth roller front rest. Hard substance between layers of fabric in loom cloth roll. Coarse temples are used, Temple rolls not properly set. A simulated sample of a hole in a silk fabric is shown in the figure 4.



**Fig 3: Stains in a Fabric**



**Fig 4: Hole in a dhoti**

##### 3.1.7 Selvedge Defects

- i. Ends breaking at Selvedge
- ii. Holes at selvedge (Temple Holes). Improper draw-in reed. Selvedges running slacker than body warp. Harsh picking. Big knots in selvedge yarn. Pins or rings or temple broken.
- iii. Slack selvedge (loose selvedge). If count in selvedge yarn is too coarse.
- iv. Corded Selvedge: Due to wrong drawing when the selvedge ends break.
- v. Torn Selvedge: Left Hand temple in place of right hand temple. One side temple not rotating, shuttle tip burred or broken. Loose or cut emery sheet on the emery roll at the edge.
- vi. Un-even selvedge
- vii. Curling selvedge
- viii. Loopy selvedge



**Fig 5: Selvedge Defects**

### 3.2 Handling Defects

These types of defects occur in a silk fabric mainly due to the poor handling of the silk cloths either by the customer or the sales person (see figure 6). Most of such defects are not rectifiable.



**Fig 6: Handling Defect**

## 4. Defect Detection System

Defect inspection in fabrics is of great importance to improve the quality [26]. Digital image processing methods have been developed for defect detection for past few years, and an elaborate discussion on the various techniques are available in [3, 4, 5, 6 & 7].

### 4.1 Texture Analysis

Texture analysis is used in many applications field like textile industrial, agricultural, remote sensing and biomedical [8] surface inspection. For example, identification of defects in textile fabrics, disease identification in human organs, classification and segmentation of satellite imagery, segmentation of textured regions in document analysis, and many more. The major issues in the real world textures are not uniform due to changes in orientation, size or other visual appearance and also the measurement of texture features are very high computational complexity.

Texture is the repetition of image patterns, which may be perceived as being directional or non-directional, smooth or rough, coarse or fine, regular or irregular, etc.

### 4.2 Fabric Texture Analysis

The fabric texture usually is made of the repetition arrangement of warp and weft and so image processing techniques can be used for defect detection [14]. Textile Fabric materials are used to prepare different categories and types of fabric products in the textile industry. Natural fabric and synthetic fabric are the two different classification of textile fabric. Synthetic fabrics are fairly new and have evolved with the continuous growth in textile industry.

Some sensor and microcontroller based designs have been carried out in [20, 21 & 23], which limits its defect detection to only a few, when compared to that of the various defects as listed out in [2]. Basic Fourier transformation can be used for modeling the woven fabrics as in [9, 19 & 22]. In some cases, a motif based defect detection in a patterned fabric [10]. Optimal Gabor Filters can be used for detecting the defects in the fabrics [11], along with textural models [24] and structural approaches [25].

With the advancements in the Wavelet Transforms, some researchers have experimented in using them for fault segmentation [12, 13]. This paper deals with the texture features in an image which can be further extended and used for the classification methodology as discussed in [14]. An experiment was also made by Paramasivam and et.al in [16 & 17] to implement the DWT modeled for fabric defect detection in a NIOS II Processor.

### 3.2.1 Feature Extraction MRCSF:

MRCSF [18 & 27] refers to Multi Resolution Combined Statistical and Spatial Frequency Method. It is a combination of first order statistical features (like energy, mean, standard deviation and variance) second order statistical features (MRFM, GLCM) [28 & 30] and Spatial Frequency for Multi Resolution Analysis

### 3.2.2 Markov Random Field Matrix (MRFM)

Markov Random Field theory is a branch of probability theory for analyzing the spatial or contextual dependencies of physical phenomena. F is said to be a Markov random field with respect to a neighborhood system N if and only if the following conditions are satisfied [29]

1. Positivity :  $P(F) > 0$  for all F.
2. Markovianity :  $P(F)$  all points in the lattice except  $P(F(i))$  neighbors of (i).
3. Homogeneity :  $P(F(i))$  neighbors of (i) depends only on the configuration of neighbors and its translation invariant.

This is a parametric approach where the texture is modeled as a Markov Random Field. First the type of neighborhood is chosen and then, the parameters on which functions depend characteristic the texture. These are called Markov Parameters. MRF Matrix is constructed from the 9 MRF parameters ( $\beta_1, \beta_2, \beta_3, \beta_4, \gamma_1, \gamma_2, \gamma_3, \gamma_4$  and  $\xi$ ).

MRF parameters are extracted in a 3x3 size matrix from an image at gray-level. The procedure consists of the following steps:

- (1) Find the relationship between the center pixel and its nearest neighbors in the 3x3 matrix by making use of the equations from (1) to (34).
- (2) Obtain 9 different MRF parameters from the 8 neighborhood system.
- (3) The parameter of  $\beta$  depends on two pixel relationships,  $\gamma$  depends on three pixel relationship and  $\xi$  depends on four pixel relationship.
- (4) MRF parameter matrix [M] output contains 9 parameters so the size is  $1 \times 9$ . Obtain the transpose of M matrix [ $M^T$ ] and multiply it with M matrix. It provides  $9 \times 9$  size MRF matrix.
- (5) Obtain MRF features from the MRF matrix.

$i_1$	$i_2$	$i_3$
$i_8$	$i$	$i_4$
$i_7$	$i_6$	$i_5$

**Fig 7: Pixel i and its eight neighbors in the second order neighborhood system**

Nine different MRF parameters are extracted from the eight neighborhood system shown in Figure 7.

$$M = [\beta_1, \beta_2, \beta_3, \beta_4, \gamma_1, \gamma_2, \gamma_3, \gamma_4, \xi] \quad (1)$$

The procedure for determining the values for  $\beta_1, \beta_2, \beta_3, \beta_4, \gamma_1, \gamma_2, \gamma_3, \gamma_4$  and  $\xi$  is given below.

$$\beta_1 = \beta_{11} + \beta_{12} \quad (2)$$

where

$$\beta_{11} = \begin{cases} 1 & \text{if } f_i = f_8 \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

$$\beta_{12} = \begin{cases} 1 & \text{if } f_i = f_4 \\ 0 & \text{otherwise} \end{cases} \quad (4)$$

$$\beta_2 = \beta_{21} + \beta_{22} \quad (5)$$

where

$$\beta_{21} = \begin{cases} 1 & \text{if } f_i = f_2 \\ 0 & \text{otherwise} \end{cases} \quad (6)$$

$$\beta_{22} = \begin{cases} 1 & \text{if } f_i = f_6 \\ 0 & \text{otherwise} \end{cases} \quad (7)$$

$$\beta_3 = \beta_{31} + \beta_{32} \quad (8)$$

where

$$\beta_{31} = \begin{cases} 1 & \text{if } f_i = f_1 \\ 0 & \text{otherwise} \end{cases} \quad (9)$$

$$\beta_{32} = \begin{cases} 1 & \text{if } f_i = f_5 \\ 0 & \text{otherwise} \end{cases} \quad (10)$$

$$\beta_4 = \beta_{41} + \beta_{42} \quad (11)$$

where

$$\beta_{41} = \begin{cases} 1 & \text{if } f_i = f_3 \\ 0 & \text{otherwise} \end{cases} \quad (12)$$

$$\beta_{42} = \begin{cases} 1 & \text{if } f_i = f_7 \\ 0 & \text{otherwise} \end{cases} \quad (13)$$

$$\gamma_1 = \gamma_{11} + \gamma_{12} + \gamma_{13} \quad (14)$$

where

$$\gamma_{11} = \begin{cases} 1 & \text{if } f_i = f_1 = f_8 \\ 0 & \text{otherwise} \end{cases} \quad (15)$$

$$\gamma_{12} = \begin{cases} 1 & \text{if } f_i = f_2 = f_4 \\ 0 & \text{otherwise} \end{cases} \quad (16)$$

$$\gamma_{13} = \begin{cases} 1 & \text{if } f_i = f_5 = f_6 \\ 0 & \text{otherwise} \end{cases} \quad (17)$$

$$\gamma_2 = \gamma_{21} + \gamma_{22} + \gamma_{23} \quad (18)$$

where

$$\gamma_{21} = \begin{cases} 1 & \text{if } f_i = f_1 = f_2 \\ 0 & \text{otherwise} \end{cases} \quad (19)$$

$$\gamma_{22} = \begin{cases} 1 & \text{if } f_i = f_6 = f_8 \\ 0 & \text{otherwise} \end{cases} \quad (20)$$

$$\gamma_{23} = \begin{cases} 1 & \text{if } f_i = f_4 = f_5 \\ 0 & \text{otherwise} \end{cases} \quad (21)$$

$$\gamma_3 = \gamma_{31} + \gamma_{32} + \gamma_{33} \quad (22)$$

where

$$\gamma_{31} = \begin{cases} 1 & \text{if } f_i = f_2 = f_8 \\ 0 & \text{otherwise} \end{cases} \quad (23)$$

$$\gamma_{32} = \begin{cases} 1 & \text{if } f_i = f_3 = f_4 \\ 0 & \text{otherwise} \end{cases} \quad (24)$$

$$\gamma_{33} = \begin{cases} 1 & \text{if } f_i = f_6 = f_7 \\ 0 & \text{otherwise} \end{cases} \quad (25)$$

$$\gamma_4 = \gamma_{41} + \gamma_{42} + \gamma_{43} \quad (26)$$

where

$$\gamma_{41} = \begin{cases} 1 & \text{if } f_i = f_2 = f_8 \\ 0 & \text{otherwise} \end{cases} \quad (27)$$

$$\gamma_{42} = \begin{cases} 1 & \text{if } f_i = f_3 = f_4 \\ 0 & \text{otherwise} \end{cases} \quad (28)$$

$$\gamma_{43} = \begin{cases} 1 & \text{if } f_i = f_6 = f_7 \\ 0 & \text{otherwise} \end{cases} \quad (29)$$

$$\xi = \xi_{11} + \xi_{12} + \xi_{13} + \xi_{14} \quad (30)$$

where

$$\xi_{11} = \begin{cases} 1 & \text{if } f_i = f_1 = f_2 = f_8 \\ 0 & \text{otherwise} \end{cases} \quad (31)$$

$$\xi_{12} = \begin{cases} 1 & \text{if } f_i = f_2 = f_3 = f_4 \\ 0 & \text{otherwise} \end{cases} \quad (32)$$

$$\xi_{13} = \begin{cases} 1 & \text{if } f_i = f_6 = f_7 = f_8 \\ 0 & \text{otherwise} \end{cases} \quad (33)$$

$$\xi_{14} = \begin{cases} 1 & \text{if } f_i = f_4 = f_5 = f_6 \\ 0 & \text{otherwise} \end{cases} \quad (34)$$

$$\text{and } M(f_i, f_{N_i}) = [X(f_i, f_{i4}) + X(f_i, f_{i8}), X(f_i, f_{i2}) + X(f_i, f_{i6}), X(f_i, f_{i1}) + X(f_i, f_{i5}), X(f_i, f_{i3}) + X(f_i, f_{i7}), X(f_i, f_{i2}, f_{i4}) + X(f_i, f_{i6}, f_{i5}) + X(f_i, f_{i1}, f_{i8}), X(f_i, f_{i1}, f_{i2}) + X(f_i, f_{i4}, f_{i5}) + X(f_i, f_{i6}, f_{i8}), X(f_i, f_{i2}, f_{i8}) + X(f_i, f_{i3}, f_{i4}) + X(f_i, f_{i6}, f_{i7}), X(f_i, f_{i8}, f_{i2}) + X(f_i, f_{i4}, f_{i3}) + X(f_i, f_{i7}, f_{i6}), X(f_i, f_{i1}, f_{i2}, f_{i8}) + X(f_i, f_{i2}, f_{i3}, f_{i4}) + X(f_i, f_{i4}, f_{i5}, f_{i6}) + X(f_i, f_{i8}, f_{i7}, f_{i6})]^T \quad (35)$$

$$MRFM = M^T M(f_i, f_{N_i}) \quad (36)$$

The RHS of the first row in the equation (35) corresponds to the potential weighted by  $\beta_1$  and  $\beta_2$ , the second row by  $\beta_3$  and  $\beta_4$ , the third to sixth by  $\gamma_1, \dots, \gamma_4$ , and the last two rows by  $\xi_1$ .

The parameters to be found in extracting MRFM features are  $\beta_1, \beta_2, \beta_3, \beta_4, \gamma_1, \gamma_2, \gamma_3, \gamma_4$  and  $\xi$ . The way of MRFM parameters estimation using second order system is shown in Figure 3.9.

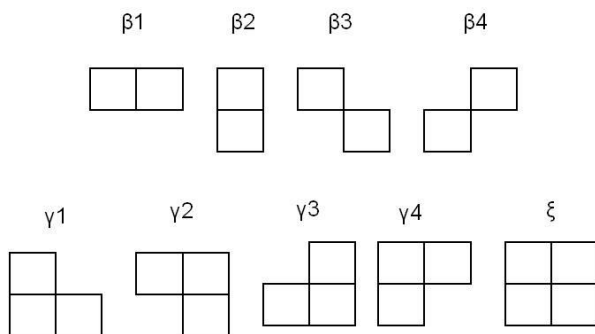


Fig 7 MRFM parameter estimation using second order system

### 3.2.3 Gray Level Co-occurrence Matrix (GLCM)

The Gray Level Co-occurrence Matrix [15]  $C[i, j]$  is defined by the first specifying a displacement vector  $d = (dx, dy)$  and counting all pairs of pixels separated by  $d$  having gray levels  $i$  and  $j$ . Count all pairs of pixels in which the first pixel has the value of  $i$  and its matching pair displaced from the first pixel by  $d$  has a value of  $j$ , and also enter this count in the  $i^{\text{th}}$  row and  $j^{\text{th}}$  column of the matrix

#### 3.2.3.1. Energy / Uniformity

$$f_1 = \sum_{i,j} C_{i,j}^2 \quad (37)$$

Where  $f_1$  is the energy feature and  $C_{i,j}$  is the co-occurrence matrix.

#### 3.2.3.2. Maximum Probability

This property gives an indication of the strongest response to the texture pattern.

$$\sum_{i=0}^{N-1} \sum_{j=0}^{M-1} \text{Max } C_{i,j} \quad (38)$$

#### 3.2.3.3. Element difference moment of order k

This descriptor has a relatively low value when high values of co-occurrence matrix are near the main diagonal because the difference is very small.

$$\sum_{i=0}^{N-1} \sum_{j=0}^{M-1} C_{i,j} (i-j)^k \quad (39)$$

#### 3.2.3.4. Inverse element difference moment of order k

$$\sum_{i=0}^{N-1} \sum_{j=0}^{M-1} \frac{C_{i,j}}{(i-j)^k} \quad (40)$$

This has an opposite effect of previous defined one.

### 5. Entropy

$$\sum_{i=0}^{N-1} \sum_{j=0}^{M-1} C_{i,j} \log(C_{i,j}) \quad (41)$$

Entropy is a measure of randomness, achieving its highest value when all elements of co-occurrence matrix are equal.

### 3.2.4 Spatial Frequency

The spatial frequency [18] is used to measure the overall information level in the regions. This is computationally simple and efficient and also can be used in real time applications. The spatial frequency for an  $M \times N$  block of an image is calculated as follows

$$SF = \sqrt{(RF)^2 + (CF)^2} \quad (42)$$

$$RF = \sqrt{\frac{1}{N^2} \sum_{m=1}^N \sum_{n=2}^N [F(m, n) - F(m, n-1)]^2} \quad (43)$$

$$CF = \sqrt{\frac{1}{N^2} \sum_{m=1}^N \sum_{n=2}^N [F(m, n) - F(m-1, n)]^2} \quad (44)$$

Where RF and CF are the row frequency and column frequency respectively. When the images get more blurred, the spatial frequency also gets reduced accordingly. Higher the value of spatial frequency, higher will be the contrast and quality of the image. In each sub band, individual pixels or group of pixels of the wavelet transform of the images are compared using spatial frequency (SF) that serves as a measure of activity at that particular scale and space. Other examples of such measures are absolute values of the pixel gray values, maximum absolute gray value of the group of pixels and the variance.

### 3.2.4 GLWM

In this method, the local texture information for a given pixel and its neighborhood is characterized by the corresponding texture unit and the global textural aspect of an image is revealed by its texture spectrum. This method extracts the textural information of an image with a more complete respect



of texture characteristics. In GLWM [30] method instead of thresholding the image transforming is made with neighborhood to a texture unit with the texture unit number under the ordering way as shown in figure 2.

A brief overview of the process of defect detection for the proposed method is shown in figure 8.

1. *Feature Extraction of original image:* This is the initial task in which the original non-defective reference samples are collected and their features are extracted using appropriate algorithm and stored in a database. Before feature extraction the sample images are wavelet transformed so that the samples are localized in both time and frequency. MRCSF Features like mean, standard deviation, energy, entropy, spatial frequency, Multi Resolution Markov Random Field Matrix and Gray Level Co occurrence Matrix (GLCM) for both the reference fabric and the fabric to be tested were extracted using MATLAB 7.5 and hence compared for classification. All the above mentioned steps are done using MATLAB Image Processing toolbox and Database Toolbox.
2. *Capturing and Feature extraction of test sample:* This part comes under the classification stage where the test samples are captured using a digital camera which is attached to a shaft which moves over the entire sample. The movement of the shaft is controlled by embedded system which employs a microcontroller. After capturing the sample images the feature are extracted in the same way as in the case of original image and stored in the library.
3. *Comparison with Library:* In this stage the stored features of the original image and the test sample are compared using the nearest neighborhood algorithm. The test samples are classified as defective or non-defective based on the comparison results.
4. *Indication of the Defects:* The obtained defect is analyzed for its type using the available database of defects and hence the defect type is displayed on the screen. The location of the defect is also displayed on the screen for the ease of the user.

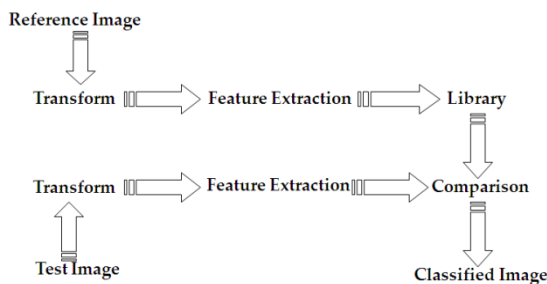


Fig 8: Defect detection system

## 5. RESULTS

Due to the absence of standard databases for the silk fabrics, a database was created with 25 reference images. These reference images were used for training the GUI designed with the algorithm. Each of these images are of the 512 x 512 size.

Various images of silk fabrics with defects as discussed in section 3.1 and 3.2 were given to the system to check if the system is capable of finding the defects present in the image.

Some of the snapshots of the same are shown in figure 9.

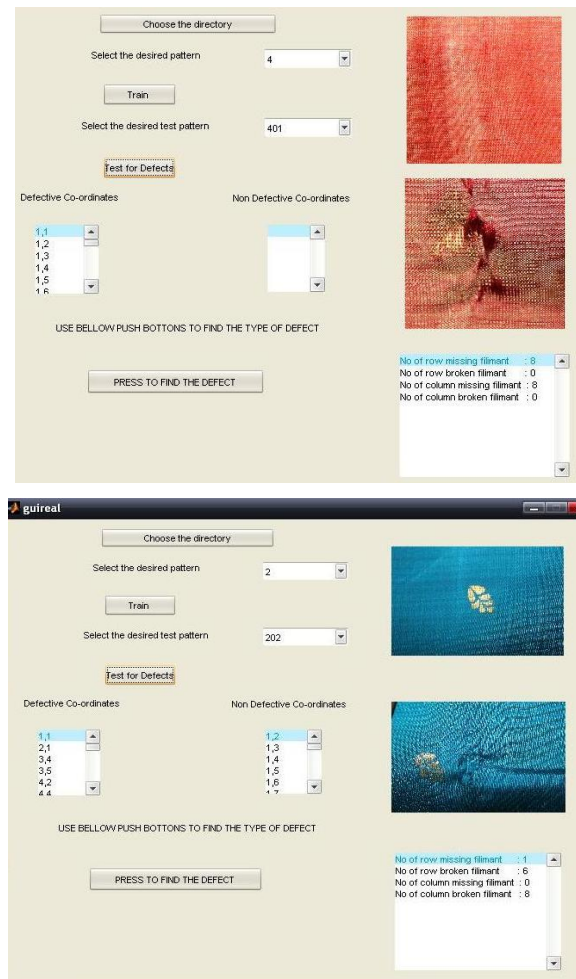


Fig 9 Snapshots of the GUI used for defect detection in silk sari

## 6. CONCLUSION

The proposed work succeeded in classifying the fabrics with repeated patterns as defective or non defective based on the MRCSF that was performed. MRCSF is a combination of first order statistical properties like mean, energy, variance and entropy, second order statistical properties like Markov Random Field Matrix, Gray level co-occurrence matrix combined with spatial frequency of Multi resolution analysis. Location and type of the defects are also identified. GLCM approach is a combination of wavelet and co-occurrence matrix features. It provides a good success rate of classification for fabrics. MRMRFM based approach is a combination of wavelet and MRFM features. In Real time Fabric the size of the sub window reduces the defect identification rate also reduces. The Classification rate of real time fabric achieved 96.6% for 25 samples.

Hardware implementation of the testing process can also be carried out keeping the cost constraint in mind. As a part of future work the same algorithm can be implemented in handloom cottage silk industries using DSP processor whenever necessary and hence forth calculate the computation time of the proposed method.

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