TEXTURE CLASSIFICATION AND DEFECT DETECTION IN USING GABOR FILTER

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بسم الله الرحمن الرحيم

Dedicate to my dearest Father and lovely Mother

(Acceptance by the Viva Voce Committee)

Title of thesis Texture Classification and defect detection using Gabor filter

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ABSTRACT

Texture Defect detection has become valuable characteristic for classifying defects in images. This research work is about texture classification and defect detection. Defect detection has mostly been viewed as texture analysis problem. Different types of techniques can be used for defect detection in textile images like local binary pattern, co-occurrence matrices, Fourier transform etc. Some of these techniques deal in frequency domain and some in time domain. We need a method which achieves optimal localization in both time and frequency domain

A technique is proposed which is based on Gabor filter for fabric defect detection. Gabor filter achieves optimal localization in both space and frequency. The strong point of Gabor filter is that it makes powerful spectrum. Gabor filter permits a joint sampling of the space and frequency domain, with a maximum joint locality in both domains that is they permit a simultaneous local analysis of both domains.

To evaluate the proposed method for fabric defect detection, the experimental results are compared with the results of morphology technique. The results show that proposed method is promising.

ACKNOWLEDGEMENT

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NOTATIONS

σ Sigma

λ Wavelength

$\int$ Integral

$\sum$ Summation

Δ Delta

Φ phi

μ Neu

Ψ psi

Π pi

F_H High frequency

F_L Low frequency

γ gamma function

ω omega

(To be submitted to the department at the time of submission of Thesis by the supervisor)

FORWARDING SHEET

The thesis entitled Texture Classification and defect detection using Gabor filter submitted by Tanveer Sajid in partial fulfillment of MS degree in Electronic Engineering with specialization in Image Processing has been completed under my guidance and supervision. Iam satisfied with the quality of student's research work and allow him to submit this thesis for further process of as per IIU rules & regulations

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CHAPTER 1

INTRODCTION

1.1 Introduction

Image texture is an important surface characteristic used to identify and recognize objects. Texture is difficult to be defined. It may be informally defined as a structure composed of a large number of more or less ordered similar patterns or structures. Textures provide the idea about the perceived smoothness, coarseness or regularity of the surface in images.

Texture classification involves deciding what texture category an observed image belongs to. In order to accomplish this, one needs to have a prior knowledge of the classes to be recognized [1].

1.2 Texture Classification

Texture classification is branch of texture analysis. Methods can be broadly following two approaches: Spatial-domain approach and Transform domain approach.

1.2.1 Spatial-Domain Approach

The approach includes the following:

1.2.1.1 Structural Texture Analysis:

This method considers texture as a composition of primitive elements arranged according to some placement rule [1]. These primitives are called texels. Extracting the texels from the natural image is a difficult task. Therefore this method has limited applications.

1.2.1.2 Statistical Methods:

This is based on the various joint probabilities of gray values. Gray Level Co-occurrence Matrices (GLCM) estimate the second order statistics by counting the frequencies for all the pairs of gray values and all displacements in the input image.

1.2.1.3 Model Based Methods:

Include fitting of model like Markov random field, autoregressive, fractal and others. The estimated model parameters are used to segment and classify textures.

1.2.2 Transform-Domain Approach

This approach analyses texture in various transform domains usually implemented through various filters/filter banks. Deriche Laws were one of the pioneers of the filtering approach. He proposed nine 3x3 masks to accentuate the texture features [1]. The response of each filter mask was used to extract texture energies. More recent developments are based on Gabor filters.

1.2.2.1 Gabor Filter

Gabor filter banks have been used to extract texture features. These filters give maximum resolution in both spatial and frequency domains and are highly desirable for texture analysis [1]. There is also evidence that Gabor filters provide good models for the response profiles of many cortical cells in the human visual cortex. The Gabor filter is of the form of a 2-D Gaussian modulated complex sinusoidal in the spatial domain.

1.3 Textures with Fabric Defects

A typical definition of texture is ``one or more basic local patterns that are repeated in a periodic manner". Textures can be categorized coarse vs. smooth. For example, rough could be many things. Gritty, Sandy, rocky, bumpy, grainy, wood grainy, and many others and smooth textures are fabric, woolen, linen etc. In this thesis textures images with fabric defects have been used. Different types of fabric defects have been shown in figure 1.

Fabric can be defined as any cloth made from yarn or fibers by weaving, knitting, felting etc. Defect detection become valuable characteristic for classifying defects in images. Task of detecting defect has mostly viewed for texture analysis problem [2]. The fabric quality is affected by yarn quality or loom defects. Some type of reasons which create fabic defects in images are given below

a. The poor quality of raw materials and improper conditioning of yarn result in yarn quality defects.
b. Effects such as color or width inconsistencies, hairiness, slubs, broken ends, etc.
c. The quality test runs on the older, worn, or obsolete model weaving machines generally produce unacceptable results.
d. The fabric defects resulting from variations in the tension of one or more yarn strands are generally misread as the defects resulting from poor yarn quality
e. The weaving irregularities generated in the weaving machines due to the change in operating conditions(temperature, humidity etc)also result in various fabric defects independently of yarn quality.
f. The population of fabric defects may vary dynamically as small changes in the weaving process can result in entirely new class of fabric defects.

Some different types of texture with different defects are given in Fig. 1.

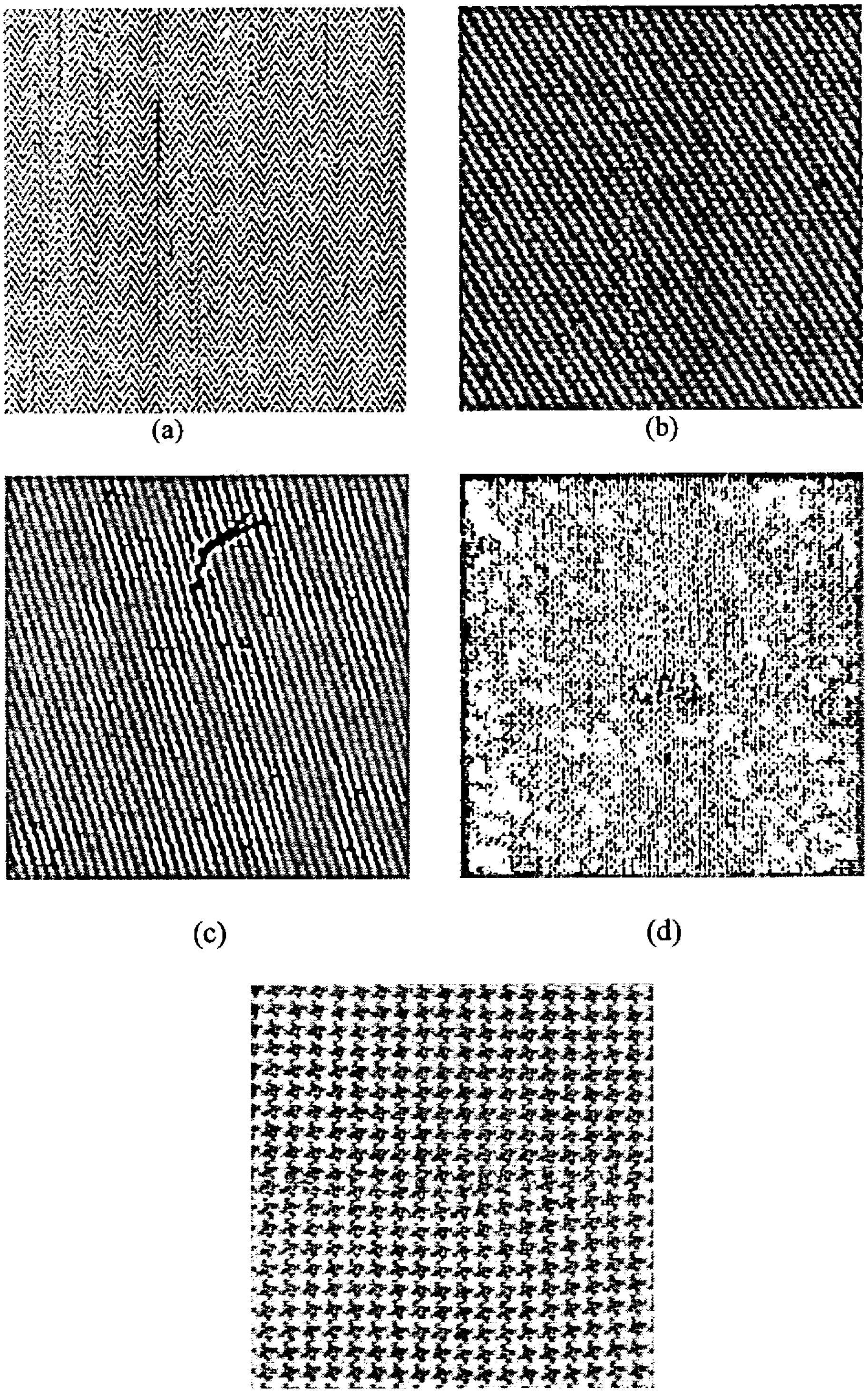


Figure 1: Fabric samples with defects (a) slub (b) missing yarn (c) big knot (d) hairiness(e) single warp

1.4 Texture Analysis Techniques for Fabric Defect Inspection

Texture is one of the most important characteristics in identifying defects or flaws. Figure1 shows some example of defects in various fabric materials. It provides important information for recognition and interpolation. In facts, the task of detecting defects has been largely viewed as a texture analysis problem [3]. We categorized texture analysis techniques use for visual inspection into four ways: statistical approaches, structural approaches, filter based approaches and model based approaches.

These approaches have explained below

1.4.1 Statistical Approaches

Statistical approaches measures spatial distribution of pixel values. They are very popular in computer vision world. Some types of statistical approaches have been explained below:-

a. Gray level Co-occurrence matrices
b. Auto correlation
c. Local binary pattern
d. Bi level thresholding
e. Cross correlation
f. Edge detection
g. Histogram properties

1.4.2 Spectral Approaches

The purpose of spectral approaches is first to extract texture primitives and seconly to generalize the spatial displacement rules [3]. The primitives can be simple as individual pixels or a region contatining uniform gray levels [3]. Some different types of spectral approaches are:

a. Discrete Fourier Transform
b. Optical Fourier Transform
c. Windowed Fourier transform
d. Wavelet Transform
e. Gabor Transform

1.4.3 Filter Base Approaches

Filter base approaches are applying filter banks on the image and compute the energy of filter responces. Various types of filter base aproaches are:

a. Spatial domain filtering
b. Frequency domain filtering
c. Joint spatial and frequency domain filtering

1.4.4 Model Base Approaches

Model based approaches rely on construction of an image model that can not only be used to explain image qualities but also synthesize it as well. The model parameters captures essential percieved qualities of image [3]. Some types of Model based approaches have mentioned below.

a. Gaussian Markov random field model
b. Model based clustering

1.5 Defect Detection Using Gabor Filter

Various methods mentioned above are used for defect detection in images. Fourier transform can not be able to localize the defective region in spatial domain [7]. When the window function is in Gaussian form then Fourier transform can be well defined Gabor transform, which get optimal localization in term of spatial as well as frequency domain . Jain and Farrokhnia [7] used Gabor filter for texture segmentation and classification. Another method Gabor filter bank had been broadly used for visual inspection . kumar and Pang [5] performed fabric defect detection only by applying the real part of Gabor filter. Later on they also used class of similar Gabor functions to classify defects in fabrics. kumar and pang also performed defect detection by using imaginary part of Gabor function as an edge detector in image. Later on the method for detecting defects in fabrics automatically based on multi channel Gabor filtering were proposed.

Han and zhang [6] presented method for detecting textile images defects using Gabor filter mask. Its performance can be computed by help of group of textile defective yarn images comprises of different types of defects. Later on filters were designed on behalf of texture feature extraction optimally from defect free fabric image area using Gabor wavelet network technique.

1.6 Problem Statement and Proposed Method

Many methods can be used for texture defect detection analysis in textile fabric images and few of them are co-occurrence matrices, Fourier transform,Wavelet transform,Gabor transform. Every method has some short comings. In co-occurrence matrix there is no accepted soloution for optimizing displacement vector. Edge detection approaches mostly used for plain weaves fabric images at low resolution not for high resolution. Fourier transform is another important tool for defect detection in textile images but it deals with images in frequency domain but not in spatial domain. There is a need of a method which localizes both in spatial and frequency domain .

Most frequently used method for defect detection is Gabor filter because of its optimal spatial and frequency localization at same time [5]. In proposed method, extracted features are based on Gabor filters showing almost uniform coverage about frequency domain. The strong plu s point about Gabor filter is m aking of very flexible power spectrum partition. It localize in spatial and frequency domain at the same time. This method gives better performance than any other technique.

1.7 Thesis Objective

The objective of research is defect detection of fabric defective texture images using 2-D circular Gabor filter technique with k mean clustering method and improve the performance of algorithm for efficient detection in image. At the end performaces of segmented images have judged by statistical parameters like mean,standard deviation, root mean squares and entropy of each image and select the best segmented images results .

1.8 Organization of Thesis

In this thesis all the chapters are ; chapter one is about introduction of research work. In chapter two literature review is discussed which is mainly about defect detection techniques. Chapter three comprises of following topics : 2-D Gabor filter, Circular Gabor filter, Gaussian window, selection of G abor filter par ameters, Gabor filter in spatial domain and frequency domaun. Chapter four is about clustering and morphology technique. Chapter five is about proposed method. In chapter six results are discussed. Last chapter is conclusion and future work.

CHAPTER 2

DEFECT DETECTION APPROACHES

Different techniques used for defect detections in images are discussed in this chapter. First approach is statistical approach comprises of gray level co-occurrence matrices, local binary pattern, cross correlation, auto correlation, edge detection techniques etc. Second approach is spectral approach. Third approach is filter based approach comprises of spatial and frequency domain techniques and join spatial-frequency domain technique. Fouth approach model base approach comprised of Gaussian Markov random field. More detail of these approaches are given below

2.1 Statistical Approaches

Statistical approaches measures spatial distribution of pixel values. Statistical approaches are very popular in computer vision world. Few statistical approches are dicussed below.

2.1.1 Co-Occurrence Matrices

Spatial gray level co-occurrence Matrices (GLCM) [4] also name as spatial gray level dependence matrix. Features like energy, entropy, contrast and correlation can determine with the help of GLCM. It's based on repetitive occurrence of different grey level configurations in a texture. Spatial gray level co-occurrence matrix (SGLCM), gray level dependent matrix (GLDM), gray level difference method (GLD) are used for defect detection in surface, fabric and wood textures. GLCM method can face number of shortcomings [3]. Generally there is no accepted solution for optimizing the displacement vector. To handle this problem, reduce number of grey levels to keep the size of matrix manageable. GLCM matrix gives poor performance as compare to filtering based method and MRF techniques.

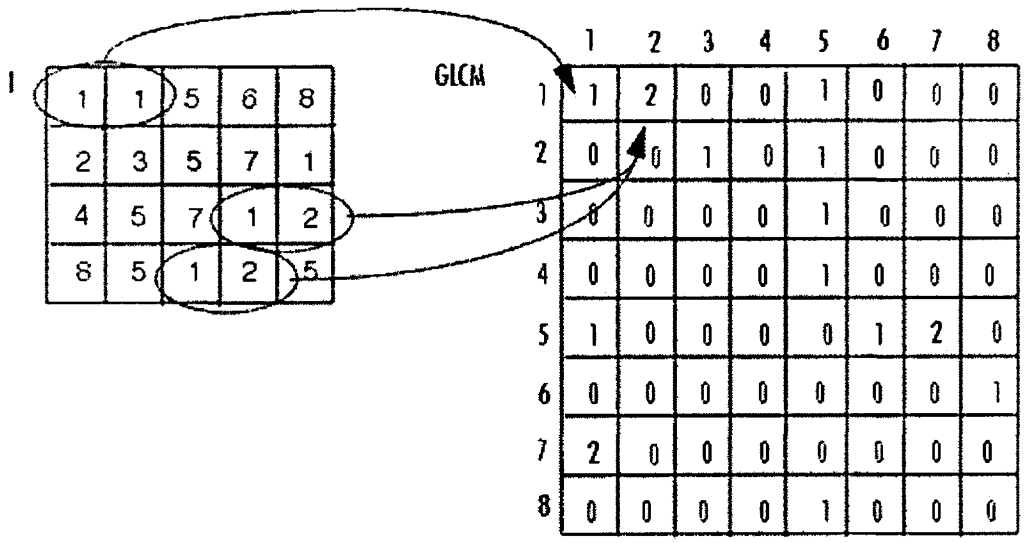


Figure 2: Gray co-matrix calculates the first three values in a GLCM

In the output GLCM, element (1, 1) contains the value 1because there is only one instance in the input image where two horizontally adjacent pixels have the values 1 and 1 respectively. GLCM (1, 2) contains the value 2 because there are two instances where two horizontally adjacent pixels have the values 1 and 2. Element (1, 3) in the GLCM has the value 0 because there are no instances of two horizontally adjacent pixels with the values 1 and 3. Gray co-matrix continues processing the input image, scanning the image for other pixel pairs (*i, j*) and recording the sums in the corresponding elements of the GLCM

2.1.2 Autocorrelation

Auto correlation method mostly applied where textures are repetitive such as textile, wood and fabric. Autocorrelation method measures correlation between the image itself and image translated with displacement vector [3]. The autocorrelation function $\rho(dr, dc)$ for Displacement $d = (dr, dc)$ is given by

$$\rho(dr,dc) = \frac{\sum_{r=0}^{N}\sum_{c=0}^{N} I[r,c]I[r+dr,c+dc]}{\sum_{r=0}^{N}\sum_{c=0}^{N} I^2[r,c]} \tag{2.1}$$

$$= \frac{\sum_{r=0}^{N}\sum_{c=0}^{N} I[r,c]*I_d[r,c]}{\sum_{r=0}^{N}\sum_{c=0}^{N} I[r,c]*I[r,c]}$$

2.1.3 Local Binary Pattern(LBP)

This technique can be used for detection in local images contrast. LBP chooses the gray level of the centre pixel of the sliding window as a threshold for surrounding neighbor' hood pixels [4].

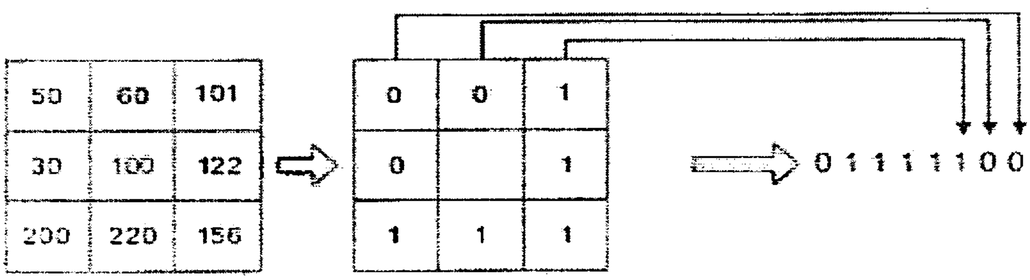


Figure 3: Local binary pattern integral image for fast extraction

2.1.4 Bi Level Thresholding

Bi-level thresholding can be applied to detect high contrast defects. Bi-level thresholding technique performs better as compare to different techniques used for defect detection [3]. When defect occurs in image then signal level moves up or down locally. Up or down in the signal indicates the defect in the image and this defect captures when the signal crosses a decision threshold. Bi level thresholding technique performs better when web is covered by fine and complex pattern [4].

Figure 4: Thresholding of Lena image (a) Original image (b) Threshold image

2.1.5 Cross Correlation

Cross correlation can be used for comparing or locating feature in image that find in another image. Cross correlation method provides accurate measurement of similarity between two images [3]. Change in resulting image indicate the presence of defects Continuous functions like f and g, the cross-correlation can be written as:

$$(f * g)(t) \stackrel{def}{=} \int_{-\infty}^{\infty} f^*(\tau) g(t+\tau) d\tau \tag{2.2}$$

In eq (2.2) f * indicates the complex conjugate of f. Equation mentioned below indicates discrete and cross-correlation function to be similar.

$$(f * g)[n] \stackrel{def}{=} \int_{m=-\infty}^{\infty} f^*[m] g[n+m] \tag{2.3}$$

This technique can work like technique of convolution of two functions

2.1.6 Edge Detection

Edge detection consists of three steps. First step is about filtering the images. Sometimes images are corrupted by noise like salt and pepper, impulse and Gaussian noise. Remove noise from images. Second enhance the image. Enhancement can be used to monitor the behavior of change in intensity in the neighbor hood of point. Third step is to remove non zero values which are not considered as edges for images. Methods like frequency, thresholding helps us in this regard.

Edges can be detected either like micro and macro edges. Micro edges can be detected by small edge operators. While Macro edges can be detected with large edge operators. The gray level patterns in image represents the line, spots, edges and other spatial discontinuities in the image [3]. These features can commonly used for detecting defects in fabric images. Sobel, Canny, Robert operators can be used for edge detection in images. Laplacian of Gaussian functions (LOG), zero crossing are some other masks also used for edge detection in images. The mostly used operator's canny, Sobel, Roberts for edge detection have shown in fig 2.2.

-1	0	+1
-1	0	+1
-1	0	+1

G_X

+1	+1	+1
0	0	0
-1	-1	-1

G_Y

$|G| = \sqrt{G_X^2 + G_Y^2}$ $\quad (|G| = |G_X| + |G_Y|)$

(a)

+1	+2	+1
0	0	0
-1	-2	-1

G_X

-1	0	+1
-2	0	+2
-1	0	+1

G_Y

$|G| = \sqrt{G_X^2 + G_Y^2}$ $\quad (|G| = |G_X| + |G_Y|)$

(b)

+1	0
0	-1

G_X

0	+1
-1	0

G_Y

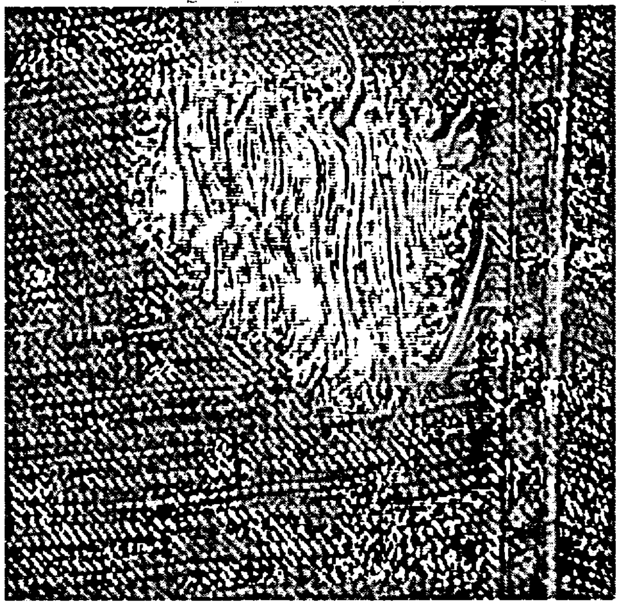
$|G| = \sqrt{G_X^2 + G_Y^2}$ $\quad (|G| = |G_X| + |G_Y|)$

(c)

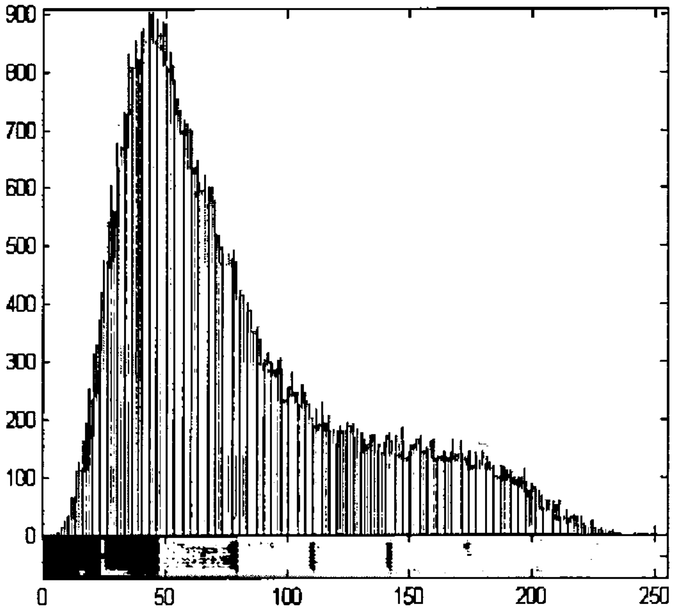
Figure 5: Masks (a) Prewitt (b) Sobel (c) Canny

2.1.7 Histogram

Histogram statistics consist of mean, geometric mean, harmonic mean, standard deviation, variance and median. There are number of histogram comparison techniques such as histogram intersection, chi-square, divergence, Bhattacharyya distance and normalized correlation [3]. Coefficient can be used for texture features. Histogram is invariant to translation and rotation and intensive to exact spatial distribution of color pixel.



(a)



(b)

Figure 6: (a) Original image (b) Histogram of image

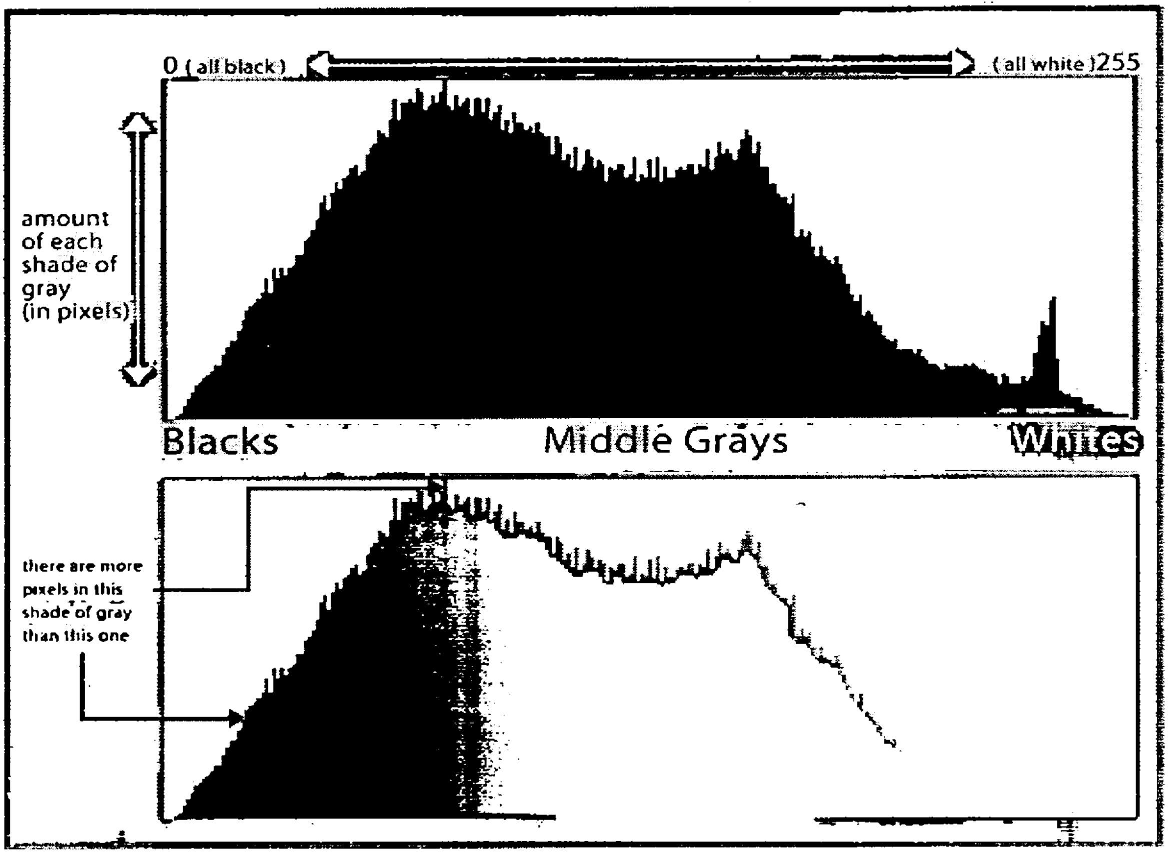


Figure 7: Histogram of gray levels intensity range

2.2 Spectral Approaches

Spectral approaches have been mostly used in computer vision for defect detection. In these approaches first step is to extract texture primitives and second to generalize the spatial placement. Random texture material unable to express in terms of primitives and displacement laws for a transfer of gray levels in the images is either stochastic [4]. Spectral type approaches unable to help for defect identification in random fabric type materials. Various approaches have been used for detection of defects in uniform texture materials. With the help of spatial and frequency domain the fabric features can be extracted from image using Fourier transform and Gabor transform in spectral type approaches.

2.2.1 Discrete Fourier Transform

This technique has ability to avoid distortion, uniform movement without rotation and best compromising solution for representation of periodic features [4]. Woolen images consist of warp and weft type patterns. Discrete Fourier models can mostly used for detecting different type of defects like missing end, peak, broken fabric and oily fabric. The technique unable to help those images in which frequency and homogenous parts linked with each other and defective images mixed with each other in large amount in Fourier domain.

2.2.2 Optical Fourier Transform

Defect detection in fabric images with the help of optical Fourier transform is easy as compare to other techniques [2]. The parameters like Brightness, first order diffraction patterns are convoluted if fabric defects occur in image. Optical system basically concern with width of fabric image which is very costly and time taking procedure.

2.2.3 Windowed Fourier Transform

Discrete Fourier transform and optical Fourier transform techniques are applied mostly for detecting global defects instead of local defects. The discrete Fourier transform and optical Fourier transform perform in frequency domain and fails to deal in spatial domain. The method for identification of defects that occurs locally needs a technique which localize in both spatial as well as frequency domain. Window Fourier transform method deals in both time domain and frequency domain.

2.2.4 Wavelet Transform

Multiresolution decomposition technique based on wavelet transform received large amount of attention of the workers for the extraction of textural features. The image can be decomposed into localized sub images at different level spatial frequencies [8]. It decompose 2D frequency spectrum of image into sub images and also high pass sub images. There are different types of wavelet transform [8]

2.24.1 Continuous Wavelet Transform

Continuous wavelet transform can be used as replacement method instead of short time Fourier transforms (STFT) to avoid resolution problem.

$$C(s,\tau) = \int_{-\infty}^{\infty} f(t)\psi(s,\tau,t).dt \tag{2.4}$$

where translational τ is proportional to time information.

2.2.4.2 Discrete Wavelet Transform

This type of wavelet transform break discrete time signal. This technique composed of filters of various cutoff frequencies can be applied for analyzing the signal at various scales. When signal pass through group of high pass filter then it monitors high frequencies. When signal pass through group of low pass filter it analyzes lower frequencies. The formula for discrete wavelet transform can be written as

$$x[n]*h[n] = \sum_{k=-\infty}^{\infty} x[k].h[n-k] \tag{2.5}$$

h[n] shows the impulse response. The convolution of signal and impulse response gives desired result

2.2.5 Gabor Transform

The Fourier transform has the property to only deal with frequency component in the signal. It is not able to localize defects in spatial domain. On the other hand Gabor transform localizes the defects both in spatial domain and frequency domain. When window function become Gaussian than windowed Fourier transform became well defined Gabor transform which achieved localization in spatial and frequency domain at same time. Gabor filter bank approach has broadly studied in visual inspection. Kumar and pang used real part of Gabor filter for defect detection. Later on they also used class of similar Gabor functions to classify defects in fabrics. Kumar and pang also performed defect detection by using imaginary Gabor function as an edge detector in image.

In fabric images Gabor filter bank technique can be applied for texture segmentation and classification of textures with dyadic coverage of the radial spatial frequency range [7]. Gabor filter is

$$g(x,y) = \left(\frac{1}{2\pi\sigma_x\sigma_y}\right)\exp\left[-\frac{1}{2}\left(\frac{x^2}{\sigma_x{}^2}+\frac{y^2}{\sigma_y{}^2}\right)+2\pi jWx\right] \tag{2.6}$$

and its Fourier transform is

$$G(u,v) = \exp\left\{-\frac{1}{2}\left[\frac{(u-W)^2}{\sigma_u{}^2}+\frac{v^2}{\sigma_v{}^2}\right]\right\} \tag{2.7}$$

2.3 Filter Based Approaches

Filter based approaches are mostly applied for calculation of energy of filter responses. Filter base approach are applying filter banks on the image and compute the energy of filter . This approach can be divided into two categories

2.3.1 Spatial Domain and Frequency Domain Techniques

In this method images are usually filtered by gradient filters to extract edges, lines, isolated dots etc.In spatial domain mostly used filters like Sobel, Canny, Laplacian, Deriche, law filters can be successively used for edge density. Kumar and Pang used FIR systems for defect detection in textile images [5]. Filter responses from defect free and defective region were collected [3].

Some other techniques are applied for filtering in the frequency domain when no exact kernel is available. Then the image can be transformed into Fourier domain by convolving with filter function at last reshaped into spatial domain saving on the spatial convolution operation [3]. Ring and wedge filters are mostly used frequency domain filters. The line defects in textile images, supposed to be defect were taken out by removing high in the recent times the multiresolution decomposition scheme achieve large attention of the researchers. The parts like energy frequency in Fourier domain applying the 1-D Hough transform. The error between stored and original picture were considered as potential defects.

2.3.2 Spatial-Frequency Methods

The problem of Fourier transform is that it cannot localize the region in spatial domain. The one way to link spatial domain with Fourier transform is through windowed Fourier transform. Gaussian function is part of window Fourier transform [4]. Gabor transform obtain optimality in both spatial and frequency domain as well.

2.4 Model Based Approaches

This technique based on Model base approaches can be used for making an image model which explain texture and synthesize it. This type of techniques has commonly applied for textile pictures having stochastic surface variations. Model based approaches are suitable for fabric images with stochastic surface variations possibly due to occurrence of fiber heap or noise.

2.4.1 Gaussian Markov Random Field (GMRF)

Gaussian Markov model is mostly used to model textile free web. The identification process was carried out as hypothesis testing problem for calculations received from GMRF model. The image is split into small window in inspection. Then a likely hood estimator test can be used for detecting defect in window occurs or not. In this process a testing image can be divided into non-overlapping sub blocks and then check each sub window one by one for defect detection [3].

2.4.2 Model Based Clustering

This technique can be used to monitor weak aligned defects that occur in fabrics. Bayesian information criterion can be used to detect presence of defects. K means clustering is one of the major type of model based clustering. Model based clustering performs well for colored images [10].

CHAPTER 3

TWO DIMENSIONAL CIRCULAR GABOR FILTER

3.1 Introduction

In image processing, a Gabor filter, named after Dennis Gabor, is a linear filter used for edge detection. Frequency and orientation representations of Gabor filters are similar to those of the human visual system, and they have been found to be particularly appropriate for texture representation and discrimination. In addition these filters have been shown to posses optimal localization properties in both spatial and frequency domain and thus are well suited for texture segmentation problems. Gabor filters have been used in many applications, such as texture segmentation, target detection, fractal dimension management, document analysis, edge detection, retina identification, image coding and image representation [35].

A 2-D Gabor filter is a Gaussian kernel function modulated by a sinusoidal plane wave. The Gabor filters are self-similar: all filters can be generated from one mother wavelet by dilation and rotation. A set of 2-D Gabor filters with different frequencies and orientations may be helpful for extracting useful features from an image. Detail of Gabor filter and 1-D and 2-D Gabor filter have explained below have explained below [35]

3.2 Gabor Filter

Gabor function is important due to multiresolution decomposition in both spatial and frequency domain. Better differentiation with the help of filter having smaller bandwidth in spatial frequency domain can be achieved. This is why Gabor filter is preferred over other methods [35].

Gabor filter gives best result when its spatial domain is complex sinusoidal Gaussian. Gabor filter with 2-D Gaussian surface which covers σ_x and σ_y having x and y direction [27] with real impulse response become

$$h(x,y)=\frac{1}{2\pi\sigma_x\sigma_y}\exp\{-\frac{1}{2}[\frac{x^2}{\sigma_x^{\ 2}}+\frac{y^2}{\sigma_y^{\ 2}}]\} \tag{3.1}$$

In term of spatial-frequency form, Gabor filter behave like two shifted Gaussian. The equation can be written as

$$H(u,v)=\exp\{-2\pi^2[\sigma_x^{\ 2}(u-u_o)+\sigma_y^{\ 2}v^2]\}+ \exp\{-2\pi^2[\sigma_x^{\ 2}(u+u_o)+\sigma_y^{\ 2}v^2]\} \tag{3.2}$$

by changing the angles the orientation can be changed.

The above equation (3.2) shows only an orientation of zero degrees with respect to the x-axis. An arbitrary rotation of the filter can be achieved spatially by rotating the spatial function in the spatial domain in the x-y plane, and in the spatial-frequency domain by rotating the frequency response function in the u-v plane.

The frequency u_0 and the rotation angle θ define the center location of the filter. By tuning u_0 and θ to different center locations we can create multiple filters that cover the spatial-frequency domain. In particular a frequency bandwidth of 1 octave is found to perform well. The frequency bandwidth, in octaves, from frequency f_1 to frequency f_2 is given by $\log(\frac{f_2}{f_1})$. It has to be noted that the frequency bandwidth increases with frequency in a logarithmic fashion.

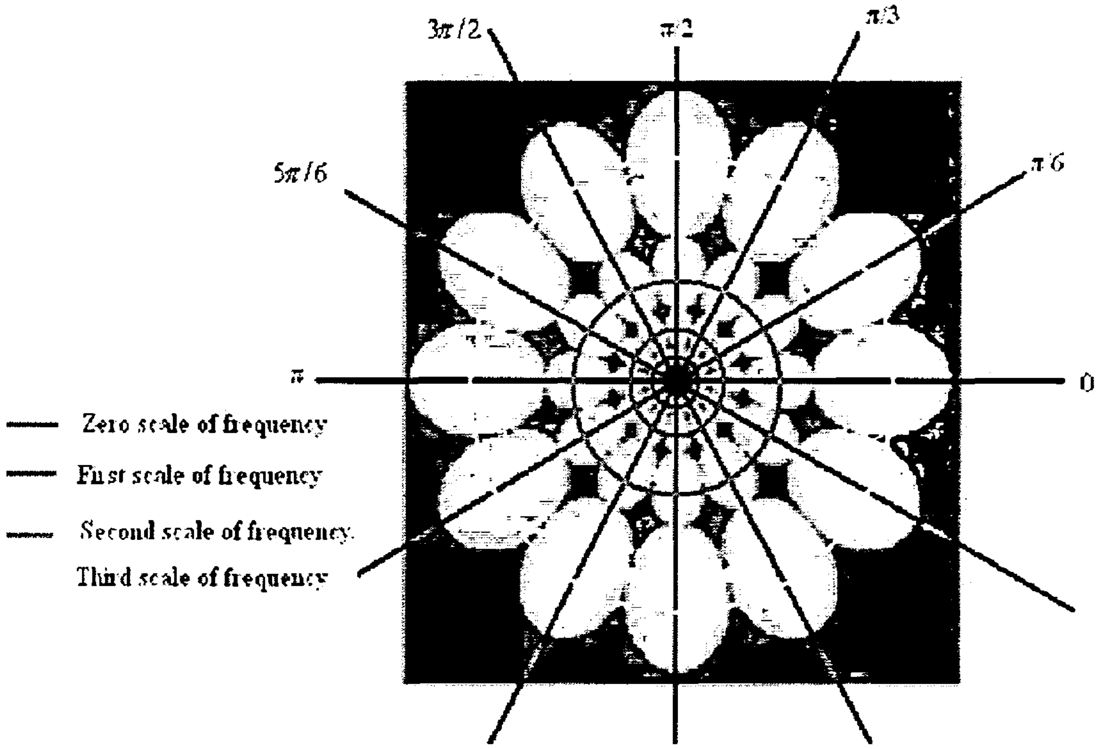
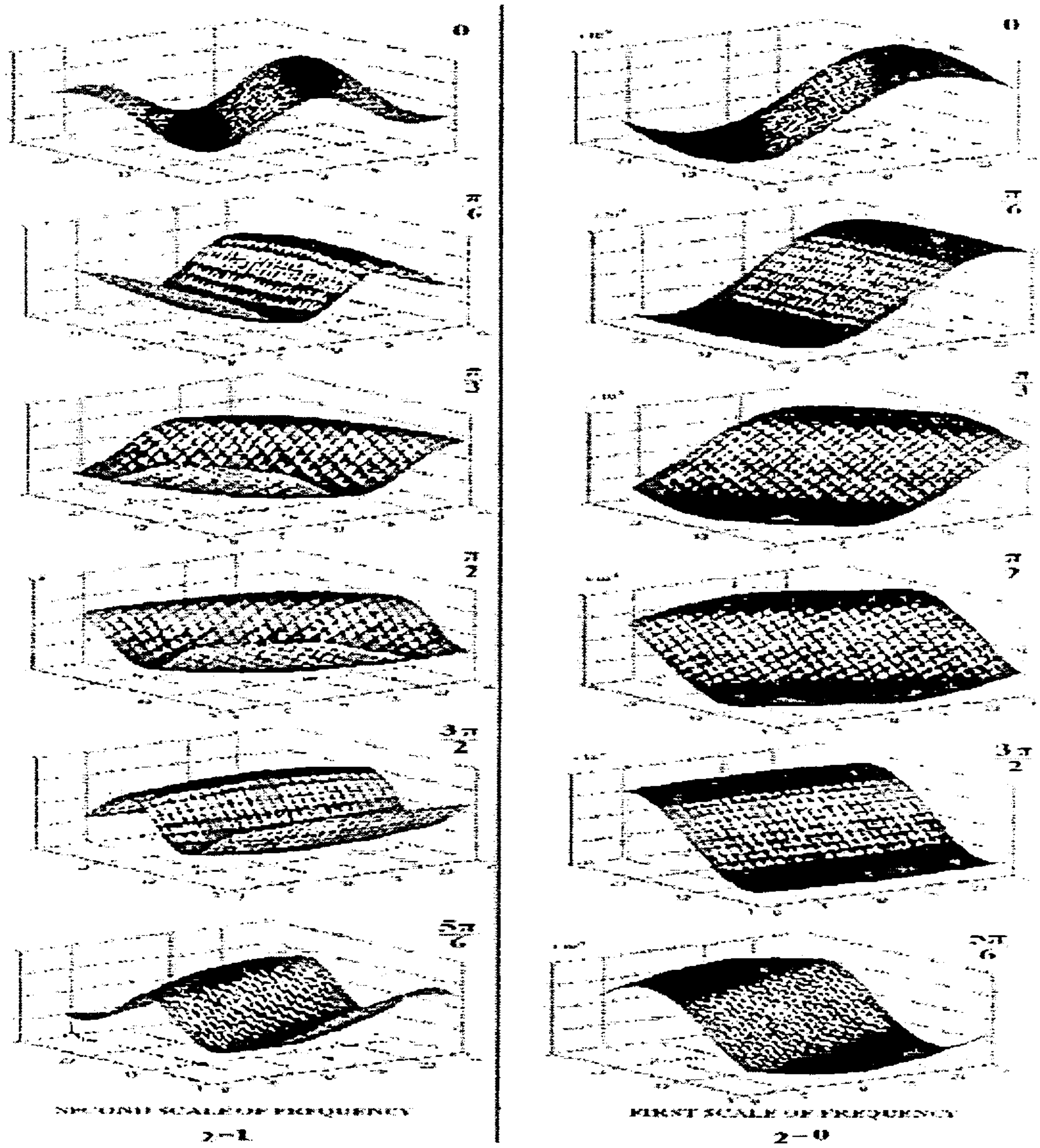
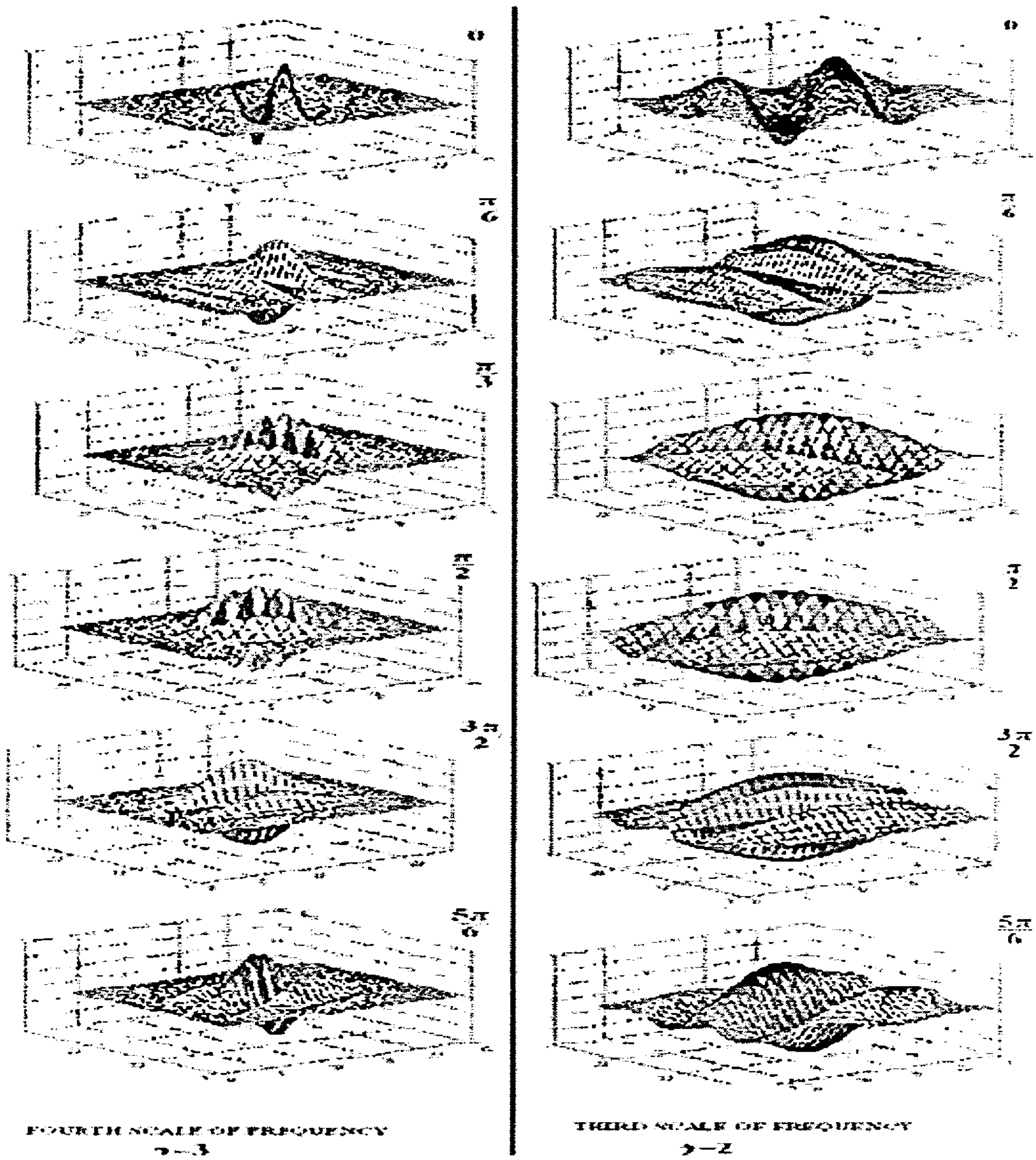


Figure 8: 2-D frequency spectrum view of Gabor filter bank design to cover frequency spectrum as much possible [35]



(a)

Figure 9: Gabor filter in spatial frequency domain with 30 degree angle orientation at different frequencies (a) f=0.125 and f=0.25 (continued)



(b)

Figure 9: Gabor filter in spatial frequency domain with 30 degree angle orientation at different frequencies (a) f=0.125 and f=0.25 (b) f=0.5 and f=1

3.3 Gabor Filter with Parameters

3.3.1 One Dimensional Gabor Filter with Parameters

One dimensional Gabor filter [39] can be represented in simple form as

$$G(x) = \cos(f(x))\exp(-(x)^2 / (\sigma)^2) \tag{3.3}$$

Where the selection of parameters are f=4 and sigma=2.

The one dimensional gabor filter consist of three parts

3.3.1.1 Cosine Part

The cosine part of one dimensional gabor filter mainly depends upon the parameters distance and frequency

3.3.1.2 Gaussian Function

Gaussian function depends upon the parameters distance and sigma. The gaussian function written in mathematical form as

$$g(x) = a\exp(-(x-b)^2 / 2c^2) \tag{3.4}$$

if a=1, b=0, c= σ then

$$g(x) = 1\exp(-(x-0)^2 / 2\sigma^2) \tag{3.5}$$

and finally gaussian smoothing function can be written as

$$g(x) = \exp(-(x)^2 / 2\sigma^2) \tag{3.6}$$

3.3.1.3 Constant

The third term involve in gabor filter is constant. It is possibly used to make the gaussian integral 1. A gaussian function has the form

$$g(x) = a\exp(-(x-b)^2 / 2c^2) \tag{3.7}$$

and the gaussian integral becomes .

$$g(x) = a * c * sqrt(pi) \tag{3.8}$$

after setting a=1, b=0, c= σ in eq (3.8)

$$g(x) = 1 * \sigma * sqrt(pi) \tag{3.9}$$

and in final form can be expressed as

$$g(x) = \sigma * sqrt(pi) \tag{3.10}$$

3.3.2 Two Dimensional Gabor Filter with Parameters

In two dimensional Gabor filter can be written as follows

$$g(x,y;\lambda,\theta,\sigma,\gamma,\varphi) = \exp(-\frac{x'^2 + \gamma^2 y'^2}{2\sigma^2})\cos(2\pi\frac{x'}{\lambda} + \varphi) \tag{3.11}$$

where

$$x' = x\cos\theta + y\sin\theta$$

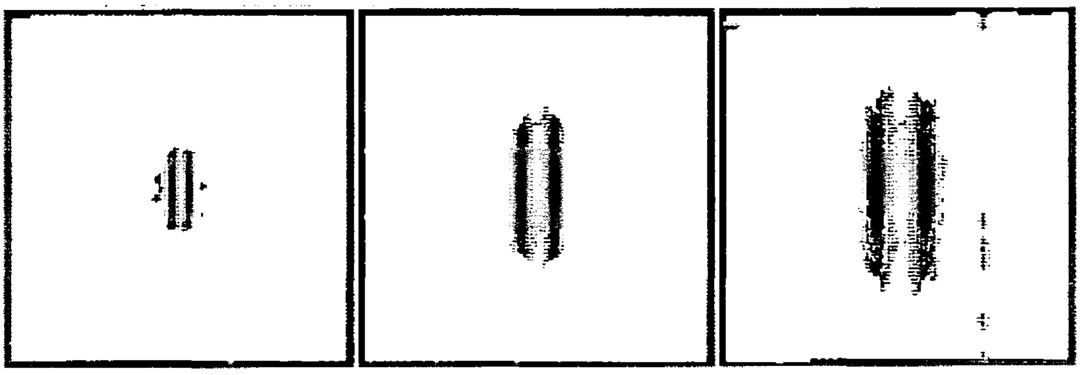
and

$$y' = -x\sin\theta + y\cos\theta$$

the calculation of parameters are given below:

3.3.2.1 Wavelength

The valid values to achieve real part of Gabor filter are equal or greater than λ [40]. But the value λ=2 cannot be used with Ψ ranges $[0^0,90^0]$. To avoid any troublesome situation λ kept smaller than one fifth of area.

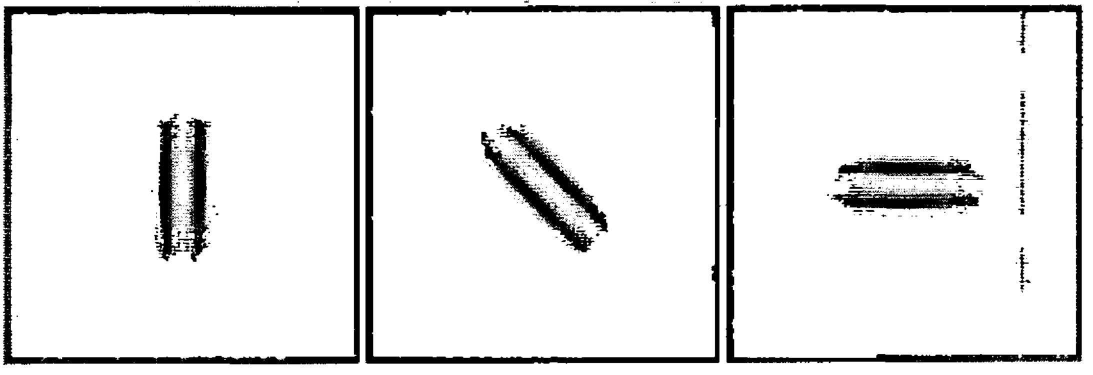


(a) (b) (c)

Figure 10: wavelength λ for these images are (a) λ=5(b) λ=10(c) λ=15.

3.3.2.2 Orientation

Its values can be represented in degrees [40]. Orientation ranges from 0^0 to 360^0. By changing values of angles the rotation of image can be changed. See in fig below.



(a) (b) (c)

Figure 11: Orientation ranges (a) 0^0 (b) 45^0 (c) 90^0

3.3.2.3 Phase Offset

Phase offset can be expressed in degrees. Valid values ranges between [-180^0,180^0]. Where the values [0^0,180^0] corresponds centre symmetric [40]. While the values at[-90^0,90^0] represent anti-symmetric. While the other values rather than these represents as as-symmetric.

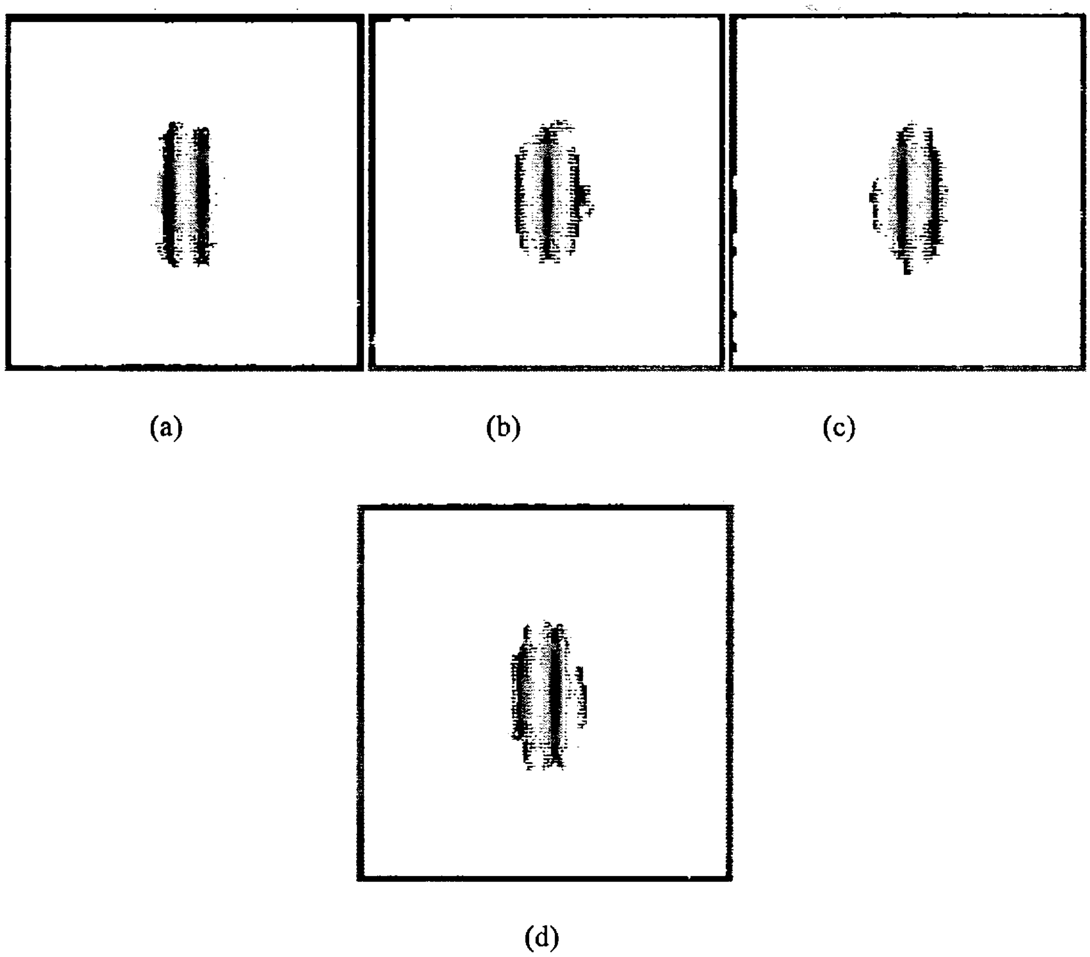
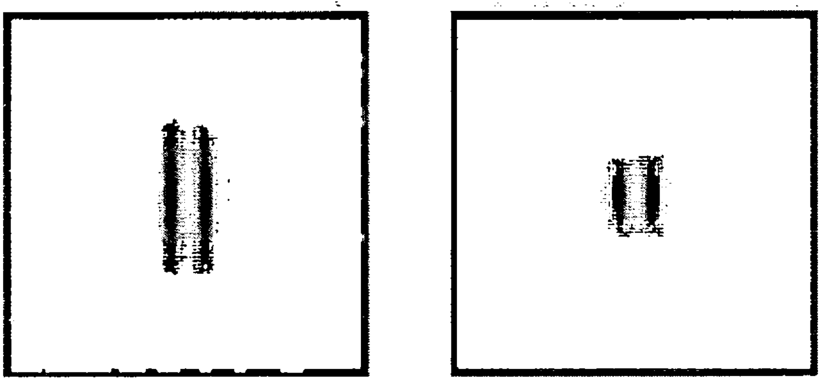


Figure 12: Phase offset for these images are (a) 0^0 (b) 180^0(c) -90^0 (d) 90^0

When single value is specified, single convolution per rotation will be calculated. From above images e.g. 0^0 and 90^0 considered default [40].

3.3.2.4 Aspect Ratio

Another name for aspect ratio is spatial aspect ratio, represents ellipiticity about Gabor function support [40]. When γ=1 it shows rotational Gabor. If γ<1 then its shows like parallel stripes. Default value is γ =0.5



(a) (b)

Figure 13: Values of aspect ratio are (a) γ=0.5 (b) γ=1

3.3.2.5 Bandwidth

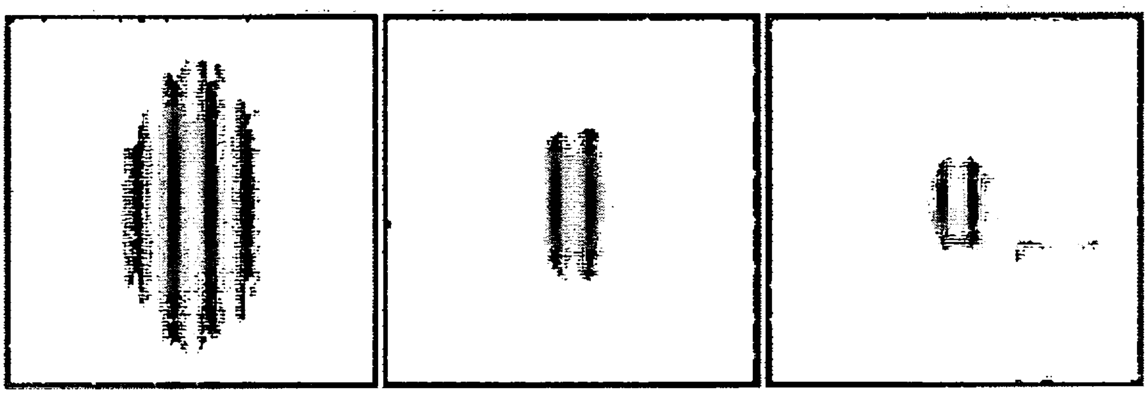
The response of Gabor filter bandwidth in spatial domain can be expressed as

$$b = \log_2 \frac{\frac{\sigma}{\lambda}\pi + \sqrt{\frac{\ln 2}{2}}}{\frac{\sigma}{\lambda}\pi - \sqrt{\frac{\ln 2}{2}}} \qquad (3.12)$$

where

$$\frac{\sigma}{\lambda}=\frac{1}{\pi}\sqrt{\frac{\ln 2}{2}}\frac{2^b+1}{2^b-1} \tag{3.13}$$

The value of sigma cannot be expressed directly. The value of sigma is changed only when the bandwidth can be changed [40]. The value of bandwidth must be written in real positive number. By choosing b=1 in which case the value of standard deviation and lambda are connected as $\sigma=0.56\lambda$.When the bandwidth is smaller the sigma should be larger



(a) (b) (c)

Figure 14: Bandwidth selected is (a) b=0.5 (b) b=1 (c) b=2

3.4 Traditional Gabor Filter

Gabor filter is the most impressive way for texture analysis. Traditional Gabor filter mainly depend on Gaussian function [16]. Mathematically can be written as

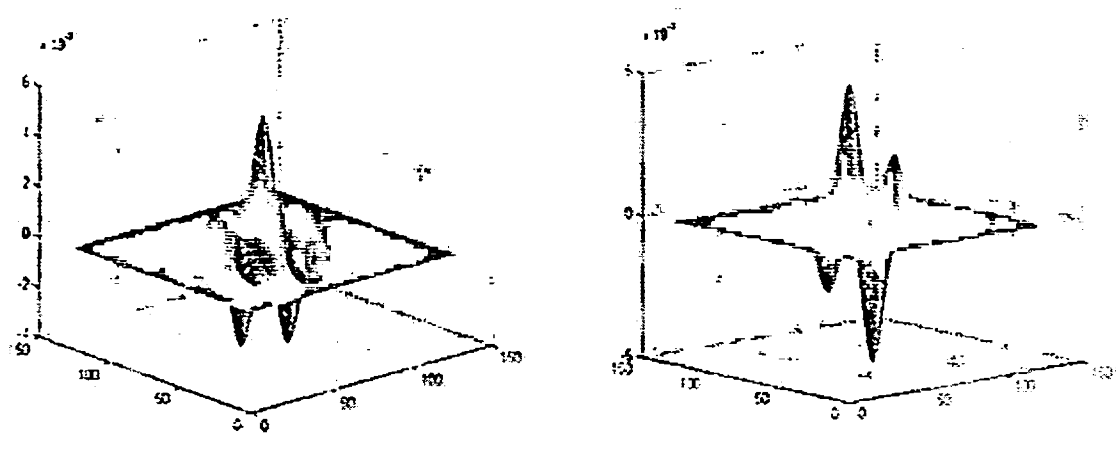
$$G(x,y)=g(x,y)\exp(2\pi if(x\cos(\theta)+y\sin(\theta))) \tag{3.14}$$

where

$$g(x,y)=\frac{1}{2\pi\sigma^2}\exp(-(x^2+y^2)/2\sigma^2 \qquad (3.15)$$

The term $g(x,y)$ denote Gaussian functions include parameters σ, f, θ. Where f represents frequency, θ represents the orientation and σ represents standard deviation [9]. Then θ ranges from 0^0 to 360^0 like this interval 0^0, $30^0, 60^0 \ldots 360^0$.

Gaussian filter is 2-D Gaussian filter in this case. Traditional Gabor filter comprises of Gaussian function modulated by sinusoid wave.



(a) (b)

Figure 15: (a) Real part of Gabor filter in spatial domain (b) Complex part of Gabor filter in spatial domain.

3.5 Circular Gabor Filter and Rotation Invariance

Usefulness of traditional Gabor filter is due to its texture direction detection. But in rotational invariant texture, the orientations become less important. The major problem of

Gabor filter is that its sinusoidal grating changes only in one direction [3 4]. If the sinusoids of Gabor filter changes in all direction than it termed as rotational Gabor filter. Mathematically rotational Gabor filter can be written as

$$G(x,y) = g(x,y)\exp(2\pi i f(\sqrt{x^2+y^2})) \tag{3.16}$$

From above f abbreviates central frequency of rotational Gabor filter. Circular Gabor filter shows clarity in term of frequency domain. The Fourier transform in frequency domain in

$$F(u,v) = \frac{\sqrt{2\pi}}{2}\alpha\exp(-\frac{(\sqrt{u^2+v^2}-F)^2}{2\alpha^2}) \tag{3.17}$$

where

$$\alpha = \frac{1}{2\pi\sigma}$$

In field of Gabor based image classification image characteristics about individual pixel has given by projection $I(x,y)$ on a complex Gabor wavelet. The equation given below

$$P = \iint I(x,y)g(x,y)\exp(i2\pi f\sqrt{x^2+y^2})dxdy \tag{3.18}$$

and

$$P' = \iint I(x',y')g(x,y)\exp(i2\pi f\sqrt{x^2+y^2})dxdy \tag{3.19}$$

where $I(x,y)$ and $I(xd,yd)$ are projections of texture surfaces on complex Gabor wavelet.

where

$$\begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} \cos\Delta\theta & \sin\Delta\theta \\ -\sin\Delta\theta & \cos\Delta\theta \end{bmatrix} \begin{bmatrix} x' \\ y' \end{bmatrix} \tag{3.20}$$

when

$$dxdy = dx'dy' \tag{3.21}$$

and

$$x^2 + y^2 = x'^2 + y'^2 \tag{3.22}$$

another way to express upper eq is

$$P' = \iint I(x' + y')g(x' + y')\exp(i2\pi F\sqrt{x'^2 + y'^2})dx'dy' \tag{3.23}$$

Above equation shows $p = p'$. Projection along Gabor wavelets remains unchanged when image is rotated [34]. Thi s property gives us the base of rotation invariance. Tremendous work has been done numerically and theoretically for parameter selection and construction of better algorithm for Gabor filter. One important conclusion is that by adjusting the spatial frequency bandwidth b great results can be achieved [35]. In human visual cortical cell, the spatial frequency bandwidth ranges from 0.5 to 2.5.

In case of rotational Gabor the value of frequency and sigma meet the condition that's command by spatial frequency bandwidth of Gabor filter

3.6 Selection of Parameters

Given below are frequency parameters used for feature extraction

$$F_L = 0.25 + 2^{(i-0.5)} / N \qquad 0 < F_L < 0.25 \tag{3.24}$$
$$F_H = 0.25 - 2^{(i-0.5)} / N \qquad 0.25 < F_H < 0.5$$
$$i = 1, 2, \ldots\ldots\ldots\log_2{}^{(N/8)}$$

Where F_H and F_L are high and low frequency components [34].

CHAPTER 4

CLUSTERING AND MORPHOLOGY TECHNIQUES

4.1 Introduction

This chapter comprises of description regarding clustering and morphology technique. Clustering can be considered the most important unsupervised learning problem; so as every other problem of this kind, it deals with finding a structure in a collection of unlabeled data. Clustering has been discussed in detail in this chapter. Morphology technique transforms the original image into another image through the interaction with the other image of certain shape and size which is known as the structure element [42]. Morphology provides a systematic approach to analyze the geometric characteristics of signals or images, and has been applied widely too many applications such as edge detection, objection segmentation, noise suppression and so on [42]. Morphology aims to extend the binary morphological operators to grey-level images. Basic morphological operations such as erosion, dilation, opening and closing are introduced.

4.2 Clustering

.Cluster can be regarded as a combination of "same" among each other and "unsame" with objects relating to other clusters. With the help of cluster analysis a group can be made which includes similar variables, like factor analysis method. There are number of ways to find cases into groups and analyze "size of data file" before adopting any method [36].

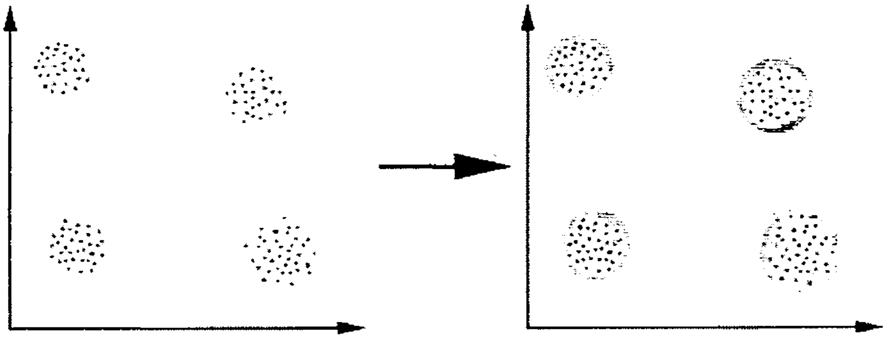


Figure 16: Clustering

4.3 Why Clustering?

Internet site google scholar [5] showed that 1660 entries with the word include data clustering showed the google website in year 2007. The huge amount of viewers tell about the importance of clustering tecnique in data analysis. Its almost impossible to explain various science branches and applications that have benefitted from this method. Clustering application can be mostly applied in image segmentation field. Clustering application can also be adopted for grouping customer into various classes due to reason of purposeful marketing. Clustering can also be used for study genome data in biology[6]

4.4 Data Clustering

Data clustering can also be considered as cluster analysis. "Another way to explain ideal cluster is a size of points close and separate from each other". Cluster can be differentiated on the basis of their size, shape, density. The noise in the data made identification of data even more complicated. Human eye is excellent example of cluster seeing object possibly in two and three dimensions as well.

4.5 Methods of Clustering

There are three different methods for clustering of data

4.5.1 Hierarchical Clustering

Hierarchical clustering reacts like agglomerative form [36]. In Agglomerative clustering technique after some repetitions same types of clusters have been. combined. Agglomerative clustering cannot help us too much. Divisive cluster start like unit cluster and ends up like individual cluster. It is clear from above that both methods fail to produce results.

Once a cluster forms, it is not broken but joined with any other cluster, but cannot divide [36]. Once in that cluster forever in that cluster. That is serious problem with agglomerative clustering.

4.5.2 Two Step Clustering

The hierarchical Clustering method and k means clustering method fails to deal with large dataset. At that stage two cluster methods can be adopted to make clusters on the behalf of categorical or continuous data [36]. Two step clustering algorithm is based on determine distance method, that gives satisfactory result if all the variables are independent. Continuous variable based on normal distribution while categorical variable based on multinomial distribution. Two step clustering involves two step

4.5.2.1 Formation of Preclusters

Preclustering objective is reducing the area of matrix which consists of distance among possible pair of cases [37]. Pre clusters can also be used as a place for raw data in hierarchical clustering. The method of precluster comprised of distance evaluation that the current case be joined with previous formed cluster for making a new precluster. After preclustering process the cases having same precluster combined as single identity.

4.5.2.2 Hierarchical Clustering of Preclusters

After making clusters hierarchically achieve number line of answers of clusters having different numbers [37].

4.6 K Means Clustering

K means clustering algorithm is 0ne of the method used for segmentation of images [37]. K means clustering does not need to calculate all possible distances. Its vary from hierarchical clustering in many ways. In k means clustering you know in advance how many numbers of clusters anybody wishes to make.

While in case of agglomerative clustering, cases summed up in present cluster [36] and remain enclosed in their cluster. K mean's symbol stands for number of clusters anybody desire to make of their own choice. That's totally depend upon on algorithm using person how many number of cluster he wants.

Further calculate cluster mean once more time, by the help of cases which assigned to cluster. Then re-arranged all cases on the basis of new group of means [37]. Performing that method again and again unless cluster means cannot change further anymore. At the end evaluate means of clusters once more and allocate the cases with permanent clusters.

Before you start with variables that comprise of large values have larger impact on the distance as compared to the smaller values have small impact on the distance. So to overcome this type of problem is to standardize variable with mean zero and standard deviation one. Then you also pick the value of 'k' means the number of cluster you want to generate K means clustering starts with a single cluster with its center as the mean of data. Split the cluster into two parts and the mean of the new cluster are iteratively trained.

The major and foremost thing about k means clustering to find k centers. That step can be complete by iterations. Take iterations one by one repeatedly. Moving with initial set of centers and modify them unless the change between two iterations is negligible [37].

When iteration ends, whole cases have given to clusters, followed by the end set of cluster centers. When whole cases will cluster then cluster centers will evaluate once more time. Explain clusters by the help of your final clusters setting.

4.6.1 K Mean Algorithm

K means basically known as unsupervised method for clustering divide incoming data points into number of sub classes' points [16]. K mean clustering is based on taking features from the data base and finds natural clustering between them.

$$v = \sum_{i=1}^{k} \sum_{x_i \in s_i} (x_i - \mu_j)^2 \tag{4.1}$$

Where k stands for number of clusters. That depends upon user that how many number of clusters he wants.Where i=1,2,3,4,..............,k and μ_i stands for mean point of all points $x_j \in s_j$.

i. Algorithm use two dimensional image as input and contain following steps
ii. Calculate the histogram of the intensities
iii. Assign a starting value to centroid with k mean intensities

iv. Repeat this process unless cluster image label cannot change further

v. Point the cluster on the behalf of distance of their intensities with centroid intensities

$$c^{(i)} = \arg\min_{j} \left\| x^{(i)} - \mu_j \right\|^2 \tag{4.2}$$

vi. Compare the new coming centroid one by one with each clustered

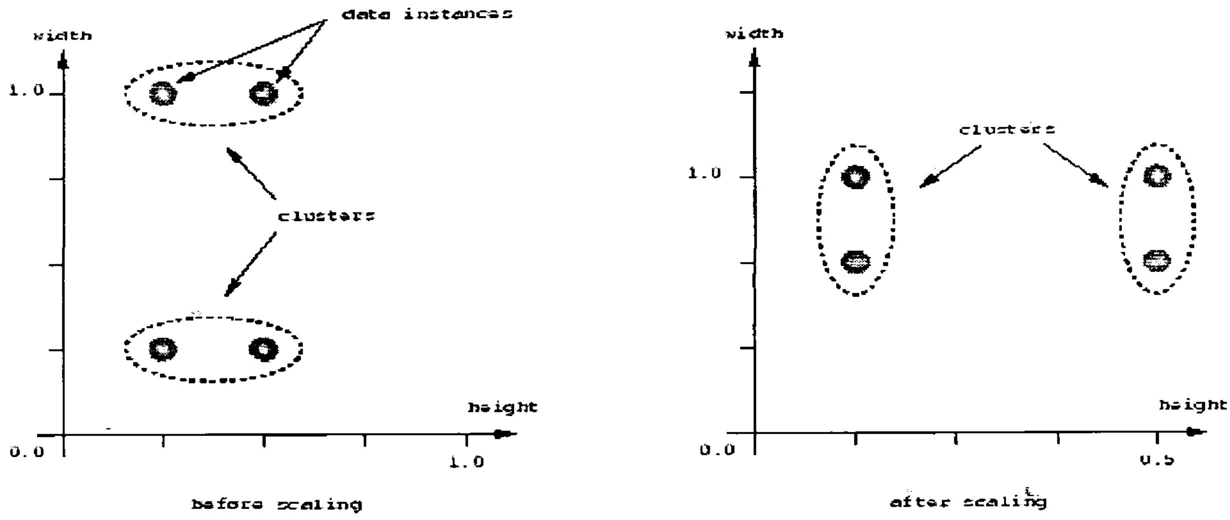
$$\mu_i = \frac{\sum_{i=1}^{m} 1\{c_{(i)} = j\} x_i}{\sum_{i=1}^{m} 1\{c_{(i)} = j\}} \tag{4.3}$$

Where k is the parameter used in this algorithm stands for number of clusters. Where are centroid intensities, term j iterate about all centroids and i iterate over all the intensities.

4.6.2 Distance Measure

The most important part of the clustering algorithm is distance measuring. Euclidian distance method is the most preferable way to find distance between two data points. Euclidian distance is very effective if the data instance vectors are all in the same physical units [16]. Formula for Euclidian distance in term of k mean algorithm is

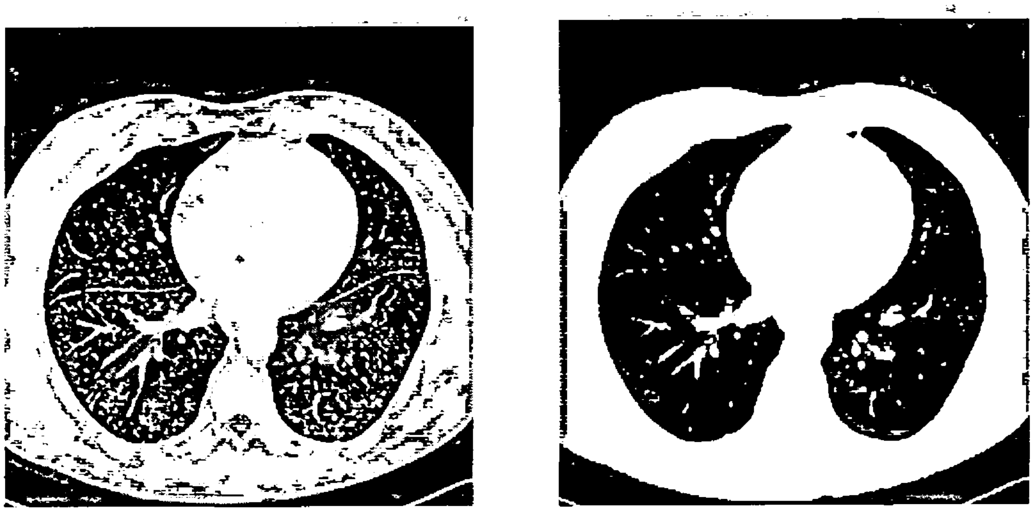
$$\rho_E(x_1, x_2) = \left\| x_1 - x_2 \right\|_2 = \left(\sum_{j=1}^{p} (x_{1j} - x_{2j})^2 \right)^{1/2} \tag{4.4}$$



(a) (b)

Figure 17: (a) k means clustering before scaling (b) k means clustering before scaling

4.6.3 K Means Image Segmentation Example



(a) (b)

Figure 18: (a) Original gray scale image (b) Three-cluster image segmentation using k mean

4.7 Morphology

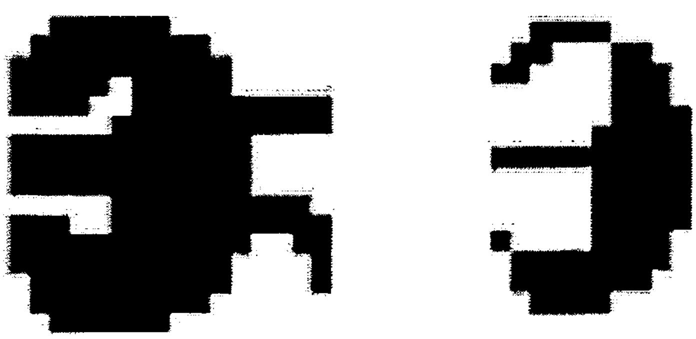
Morphology can be defined as the study of the forms of things, in particular.The morphology consists of four operations separately applied on images as shown below:

4.7.1 Erosion

Erosion is typically applied to binary images, but there are versions that work on grayscale images [42]. The basic effect of the operator on a binary image is to erode away the boundaries of regions of foreground pixels. Formula for erosion is

$$A \Theta B \tag{4.5}$$

Thus areas of foreground pixels shrink in size, and holes. The study of the forms of things, in particular within those areas becomes larger. In this process we increase the black pixel in the image making, it look thinner. Every object pixel that is touching an background pixel is changed into background pixel.



(a) (b)

Figure 19: (a) original mage (b) eroded image

4.7.2 Dilation

Dilation is one of the operators in the area of mathematical morphology, the other being erosion. It is typically applied to binary images, but there are versions that work on grayscale images. Formula for dilation is

$$A \oplus B \tag{4.6}$$

The basic effect of the operator on a binary image is to gradually enlarge the boundaries of regions of foreground pixels. Thus areas of foreground pixels grow in size while holes within those regions become smaller [42].

In dilation we increase the white pixel in the image making, it look broader. Every background pixel that is touching an object pixel is changed into an object pixel.

(a) (b)

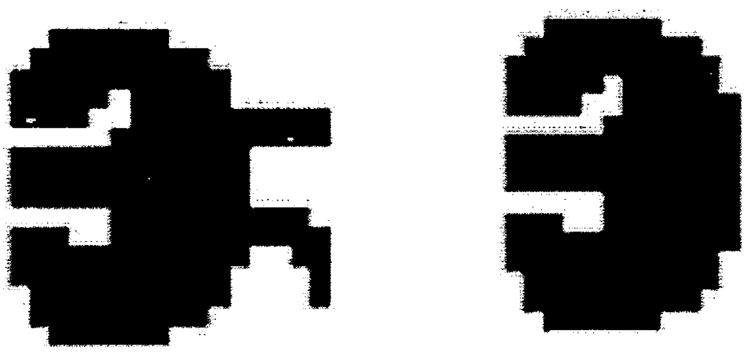
Figure 20: (a) original mage (b) dilated image

4.7.3 Opening

In morphology, opening is the dilation of the erosion of set A by structuring element B:

$$A \circ B = (A \Theta B) \oplus B \tag{4.7}$$

Where Θ and $\oplus$ denote erosion and dilation, respectively. Together with closing, the opening serves in computer vision and image processing as a basic workhorse of morphological noise removal. Opening removes small objects from the foreground (usually taken as the dark pixels) of an image, placing them in the background, while closing removes small holes in the foreground, changing small islands of background into foreground. These techniques can also be used to find specific shapes in an image [43]. The process of "opening" an image will likely smooth the edges, break narrow block connectors and remove small protrusions from a reference image. "Closing" an image will also smooth edges but will fuse narrow blocks and fill in holes [44]



(a) (b)

Figure 21: (a) original mage (b) open image

4.7.4 Closing

In mathematical morphology, the closing of a set (binary image) A by a structuring element B is the erosion of the dilation of that set,

$$A \bullet B = (A \Theta B) \oplus B \tag{4.8}$$

Where Θ and $\oplus$ denote erosion and dilation, respectively. In image processing, closing is, together with opening, the basic workhorse of morphological noise removal. Opening removes small objects, while closing removes small holes. In this process we firstly do Dilation and then Erosion. This method is used to remove the extra black pixels from the images [42]. By utilizing the processes of erosion and dilation, opening and closing is simply and extension of these applications. The process of "opening" an image will likely smooth the edges, break narrow block connectors and remove small protrusions from a reference image. Closing an image will also smooth edges but will fuse narrow blocks and fill in holes. [43]

(a) (b)

Figure 22: (a) original mage (b) close image

CHAPTER 5

PROPOSED ALGORITHM

5.1 Introduction

A proposed technique for fabric defect detection and segmentation is presented and discussed in this chapter. The proposed method comprises of mainly three steps. First step is about decomposition of input image using a Gabor filter bank. For this purpose 2-D circular Gabor filter can be used. A 2-D circular Gabor filters consist of sinusoidal plane wave of some frequency and orientation, modulated by two dimensional Gaussian function.

In Second step extraction of the features from decomposed image using non linear sigmoid function which saturates the output of this filter have been done. This sigmoid function behaves like logistic activation function which have been used in artificial neural network. After feature extraction next step is to remove noise and other undesired effect. For this purpose 2-D Gaussian function can be used which smoothes the image.

Third and final step of proposed method is clustering the pixels into number of clusters representing the texture regions. In research work k Mean clustering method can be used for this purpose. K mean clustering technique is an easy way to classify a given data set through a certain number of clusters (assume k clusters) fixed a priori. K mean clustering algorithms were discussed in detail chapter four.

After defect detection different statistical parameters like Mean, Standard Deviation, Root Mean Square and Entropy can be used for results evaluation.

5.2 Flow Chart of Proposed Algorithm

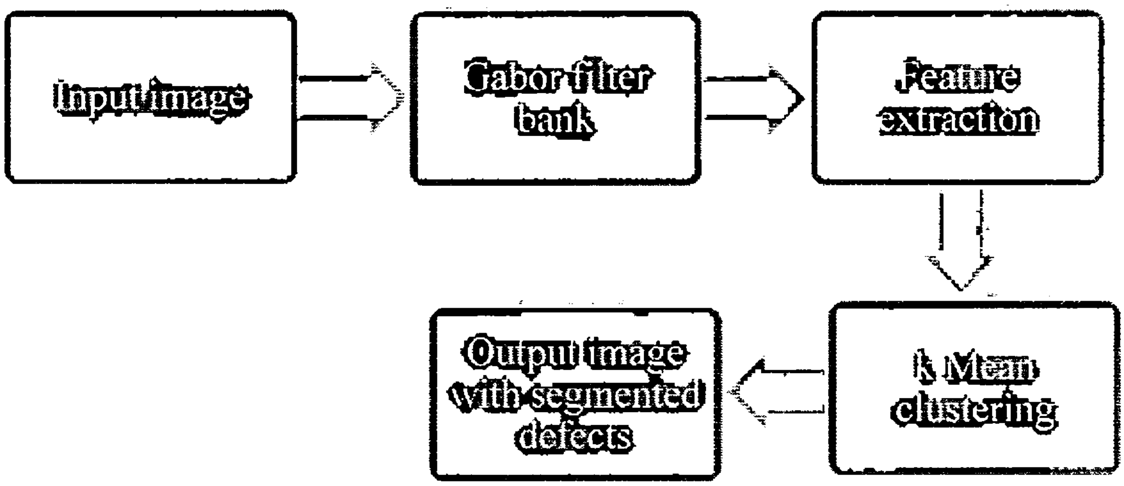


Figure 23: Flow chart of algorithm used for defect detection in textile images

Flow chart comprises of five steps. First step is to select input image. Second step is about decomposition of image by using Gabor filter banks tuned at different frequencies and orientations. Third step is to extract features from decomposed images, for this purpose sigmoid function can be used. Fourth step is to cluster the extracted features. After clustering defective segmented part can be clearly seen. Detail of all these steps have explained below

5.2.1 Gabor Filter Bank

A two dimensional Gabor filter algorithm based on sinusoidal plane wave of some frequency and orientation as well. The 2-D Gabor filter is modulated by 2-D Gaussian function. The real part of Gabor filter can be written as

$$g(x,y;\lambda,\theta,\sigma,\gamma,\varphi)=\exp\left(-\frac{x'^2+\gamma^2 y'^2}{2\sigma^2}\right)\cos\left(2\pi\frac{x'}{\lambda}+\varphi\right) \quad (6.1)$$

where

$$x' = x\cos\theta + y\sin\theta \quad (6.2)$$

and

$$y' = -x\sin\theta + y\cos\theta \quad (6.3)$$

Gabor filter in imaginary form can be written as

$$g(x,y;\lambda,\theta,\sigma,\gamma,\varphi)=\exp\left(-\frac{x'^2+\gamma^2 y'^2}{2\sigma^2}\right)\exp\left(i\left(2\pi\frac{x'}{\lambda}+\varphi\right)\right) \quad (6.4)$$

or

$$g(x,y;\lambda,\theta,\sigma,\gamma,\varphi)=\exp\left(-\frac{x'^2+\gamma^2 y'^2}{2\sigma^2}\right)\sin\left(2\pi\frac{x'}{\lambda}+\varphi\right) \quad (6.5)$$

The real part represents Gabor filter in spatial domain. In equations above represented from (6.1) to (6.6) the wavelength of cosine factor and θ represents orientation ranges from 0^0 to 360^0. Where as ψ represents phase offset measure in degrees and γ stands for aspect ratio and σ represents standard deviation of the Gaussian function. Where as λ stands for wavelength and $f = 1/\lambda$ denote spatial frequency of cosine function. Bandwidth b and ratio σ/λ can be expressed under

$$b = \log_2 \frac{\frac{\sigma}{\lambda}\pi + \sqrt{\frac{\ln 2}{2}}}{\frac{\sigma}{\lambda}\pi - \sqrt{\frac{\ln 2}{2}}} \tag{6.6}$$

where

$$\frac{\sigma}{\lambda} = \frac{1}{\pi}\sqrt{\frac{\ln 2}{2}}\frac{2^b + 1}{2^b - 1} \tag{6.7}$$

When π=0 it express the real part and π=90 represents imaginary portion. The real part become symmetric and properly satisfied algorithm needs. One thing should kept in mind that bandwidth should be expressed in octaves.

5.2.2 Feature Extraction

Use sigmoid function for feature extraction which can be written as given below

$$\tanh(\alpha t) = \frac{1 - e^{-2\alpha t}}{1 + e^{-2\alpha t}} \tag{6.8}$$

This saturates the output of the filter. Another thing for calculation is average absolute deviation for each filter. For this purpose Gaussian smoothing function can be used.

$$g(x, y) = \exp\{-\frac{x^2 + y^2}{2\sigma^2}\} \tag{6.9}$$

σ represents standard deviation evaluate size and shape of respective branch. Select σ=3σ.

5.2.3 Clustering

The algorithm finishes after last step in which clustering pixels into multiple numerous sub pixels is done. K mean clustering method can be used for segmentation process. The method summarized below

a. Hold centroids of k mean cluster.
b. Place individual sample step by step to closest centroid.
c. Evaluate cluster mean.
d. When centroids cannot change further at the end than work is done, other wise skip to the step two again.

Further more join spatial coordinates of pixel as two plus point features to keep into account.

5.3 Choice of Gabor Filter Parameters

Frequency parameter use in Gabor filter are given below

$$\begin{aligned} F_L &= 0.25 + 2^{(i-0.5)} / N \qquad 0 =< F_L < 0.5 \\ F_H &= 0.25 - 2^{(i-0.5)} / N \qquad 0.5 < F_H < 2.5 \end{aligned} \tag{6.10}$$

where

$i = 1, 2, \ldots\ldots\ldots \log_2^{(N/8)}$

For orientation in Gabor filter the angle should be used having a gap of thirty degrees $\theta = 30^0$ to $36\theta^0$ and for the choice of frequency parameter f following equations can be used.

Keep in mind the values of low and high frequencies are given below

$$0.5 < F_H < 2.5 \quad (6.11)$$

$$0 =< F_L < 0.5 \quad (6.12)$$

5.4 Statistical Parameters for Evaluation of Results

The main aim of feature extraction is to find some characteristics that distinguish between normal (standard) and defective fabrics. Statistical parameters are numerically descriptive measures of the histogram. These parameters describe the states of nature in decision problem. Therefore, statistical features such as mean, standard deviation, root mean square and entropy are used to characterize the histograms and to distinguish between normal and defective fabrics. The mathematical definitions of these features are:

5.4.1 Mean

Mean μ calculate the average values of pixels. Where N stands for total number of pixels in the image

$$MEAN = \mu = \frac{1}{N}\sum_{i=1}^{N} x_i \quad (6.13)$$

5.4.2 Standard Deviation

Standard deviation is most commonly used statistical parameter use to measure dispersion. It measure how widely spread the data set are. If data points are close to the mean then the SD is small and vice versa. Formula for standard deviation is

$$\sigma = \sqrt{\frac{\sum_{i=1}^{N}(x_i - \mu)^2}{N-1}} \quad (6.14)$$

5.4.3 Root Mean Square

The formula for measuring Root Mean Square (RMS) is given below

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2} \tag{6.15}$$

5.4.4 Entropy

Entropy is measure of un-certainty with random variable. Entropy is measure of disorder or more precisely unpredictability associated with image or information. In formula p stands for probability.

$$Entropy = -\sum_{i=1}^{N} P_i \log P_i \tag{6.16}$$

Where N stands for amount pixels contain in image

5.5 Calculate Black and White Pixels

In binary images pixels have values 0 or 1. To calculate black and white pixels by assigning 0 to white and 1 to black and calculate black and white pixels in image.

5.6 Effective Area Measurement

Effective area can be calculated by dividing defected segmented area with original gray scale image defective area.

$$\text{Effective Area (EA)} = \frac{\text{Defective Area after Segmentation in Image (DASI)}}{\text{Original Image Defective Area (OIDA)}} \tag{6.17}$$

Area will be measured in pixels

CHAPTER 6

EXPERIMENTAL RESUTS AND DISCUSSION

6.1 Introduction

The experimental resuts of algorithm are discussed and also compared with other techniques. The proposed algorithm is based on two dimensional circular Gabor with tunable frequencies and bandwidths applied on data set. To evaluate the proposed algorithm the results of proposed algorithm can be compared with the results of morphological technique.

6.2 Data set

Data set comprises of three different fabric defective images. Which were obtained from denim fabric images official website.

The first image is 256x256 denim jeans image with hairness fabric defect in it.

The second image data set is 256x256 plain cotton image with slub yarn fabric defect.

The third image is 256x256 cotton image with slub yarn fabric defect in it.

Figure 24: Jean image with fabric defect

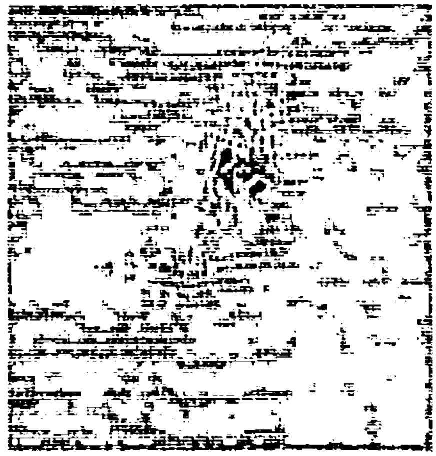


Figure 25: Plain cotton image with fabric defect

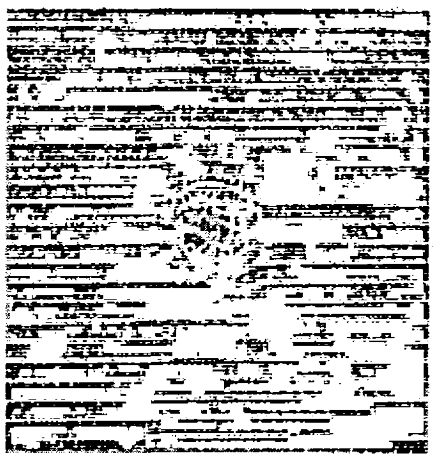
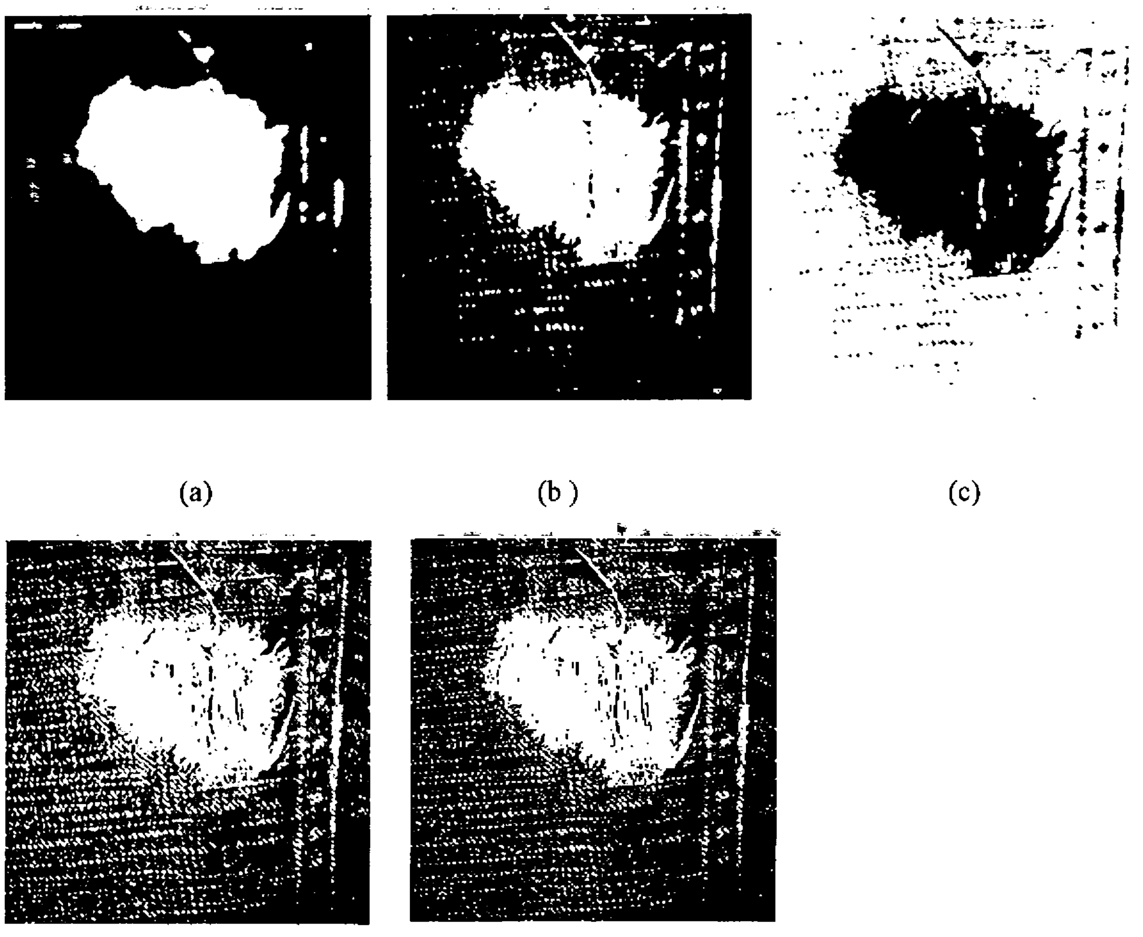


Figure 26: Cotton image with fabric defect

6.3 Experimental Results

6.3.1 Segmented Results for Jeans Image Using Gabor Filter with Frequencies Ranging from f=0.5 to 2.5

Segmented results for different frequencies have shown Figure 27 (a)-(e). The images at low frequency values give better segmented r esults. The segmented area (defective) shape is good at low frequencies and poor at higher frequencies. At f=0.5 good segmentation results have achieved



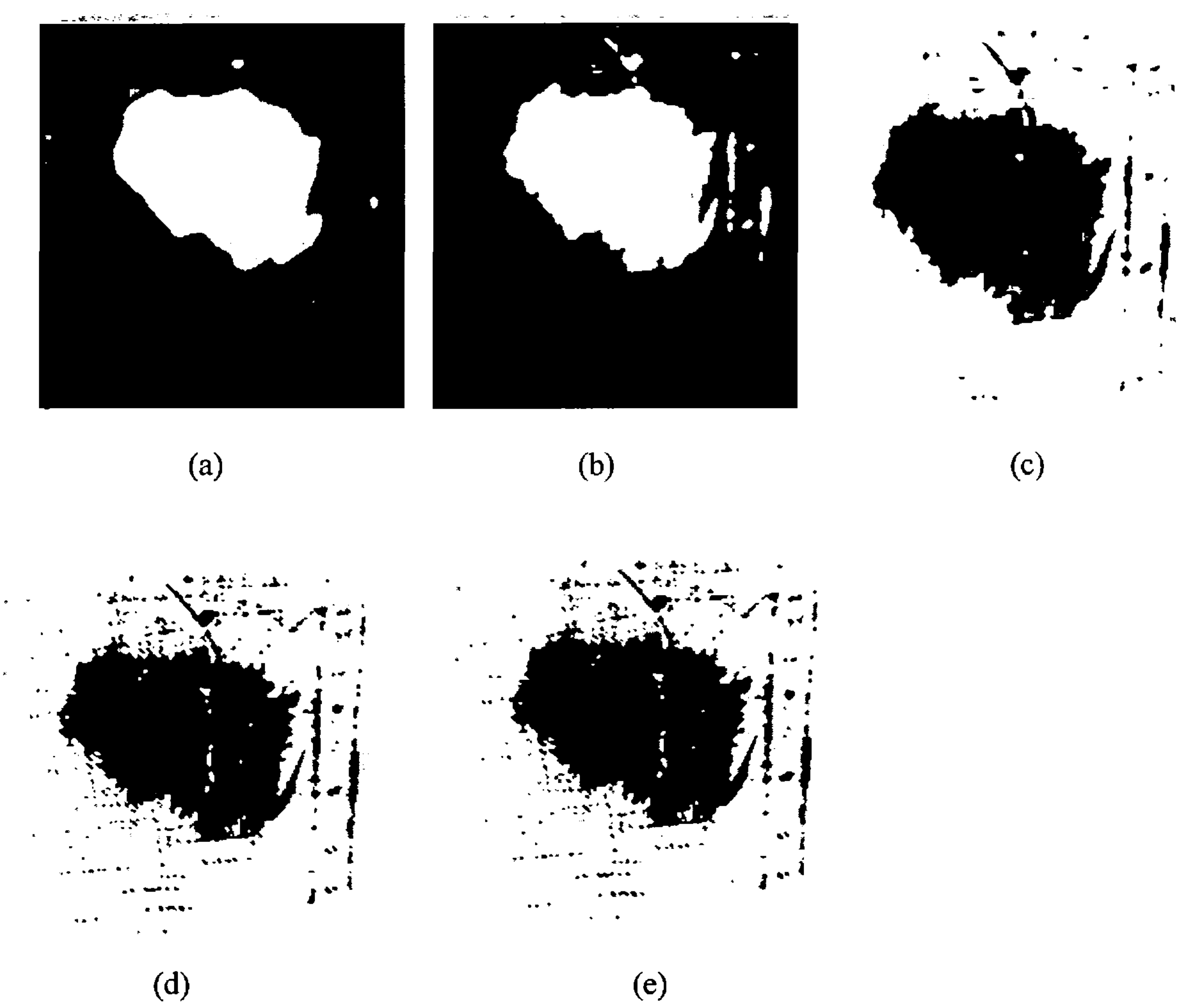
(a) (b) (c)

(d) (e)

Figure 27: Segmented Results of Jeans Image with different parameters b=0.5, k=2, γ =0.5 with frequency changes (a) f=0.5 (b) f=1 (c) f=1.5 (d) f=2 (e) f=2.5

6.3.2 Segmented Results for Jeans Image Using Gabor Filter with Bandwidth Ranging from b=0.5 to 2.5

In Figure 28 (a)-(e) results have shown at different bandwidth values ranging from b=0.5 to 2.5 by keeping frequency and gamma values constant. The results at bandwidth b=0.5 and b=1 are good. Because its segmented area is good



(a) (b) (c)

(d) (e)

Figure 28: Segmented Results of Jeans Image with different parameters=0.5, k=2, γ =0.5 with bandwidth changes (a) b=0.5 (b) b=1 (c) b=1.5 (d) b=2 (e) b=2.5

6.3.3 Segmented Results for Jeans Image Using Gabor Filter with Bandwidth Ranging from $\gamma = 0.5$ to 2.5

The segmentation results of proposed method with gamma changes from γ=0.5 to γ=2.5 by keeping frequency and bandwidth constant have shown in Figure 29 (a)-(e). The segmented result at γ=0.5 and γ=1 are good

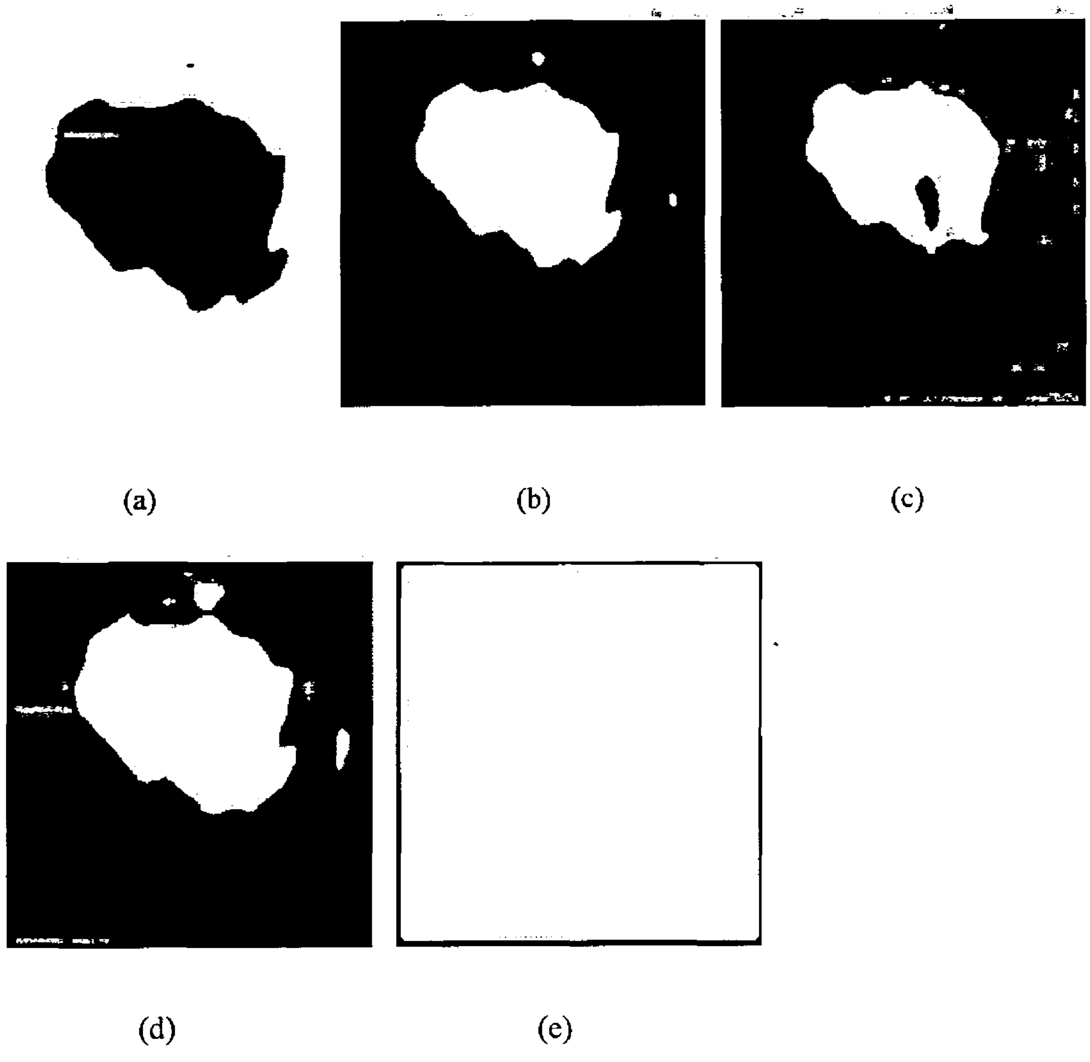


Figure 29: Segmented Results of Jeans Image with different parameters b=0.5, k=2, f =0.5 with gamma changes (a) γ=0.5 (b)γ=1 (c) γ=1.5 (d) γ=2 (e) γ=2.5

6.3.4 Segmented Results for Plain Cotton Image Using Gabor Filter with Frequencies Ranging from f=0.5 to 2.5

The results in Figure 30 is about segmentation of plain cotton image with frequencies changing from (a)-(e). The result at f=1 and f=1.5 are good because its segmented area is better than other when compare with original image.

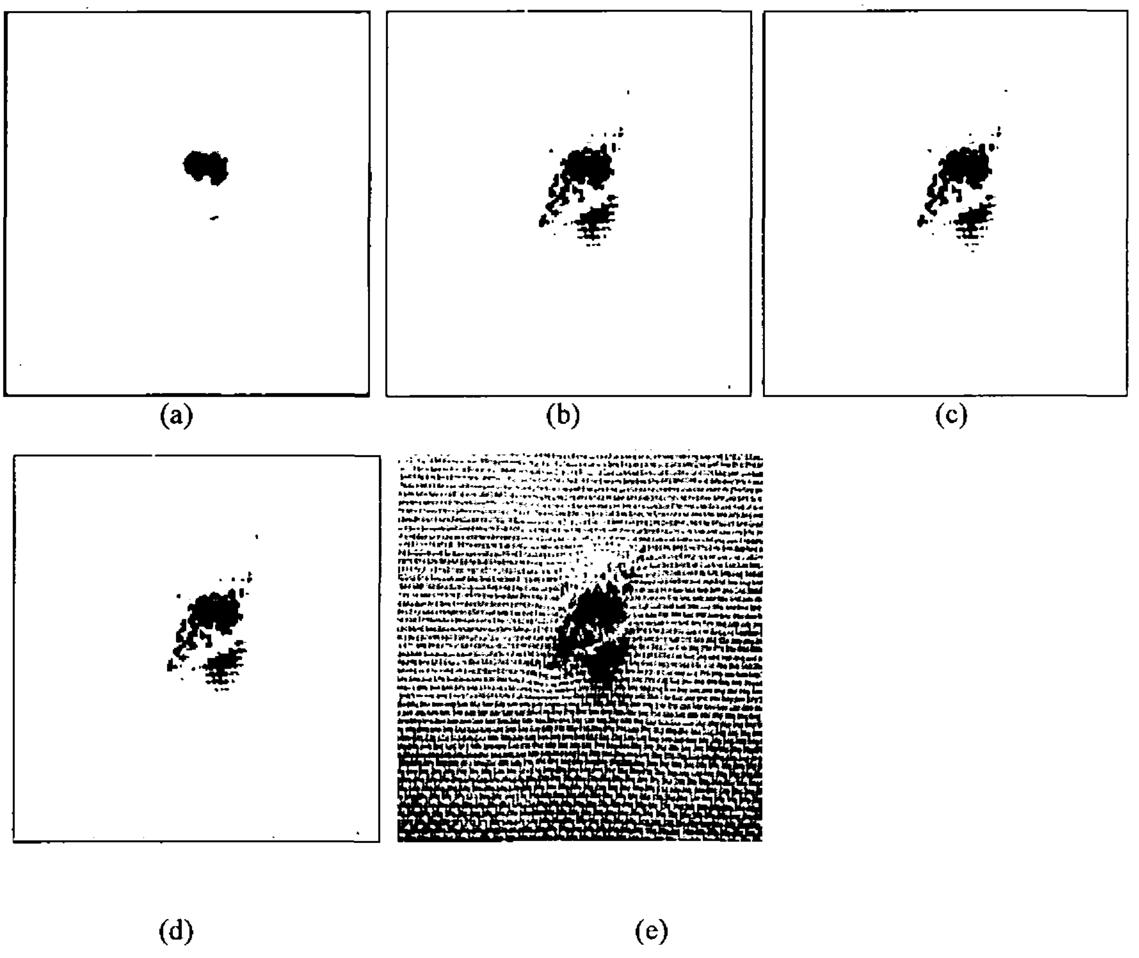


Figure 30: Segmented Results of plain cotton Image with different parametersb=0.5, k=2, γ =0.5 with frequency changes (a) f=0.5 (b)f=1 (c) f=1.5 (d) f=2 (e) f=2.

6.3.5 Segmented Results for Plain Cotton Image Using Gabor Filter with Bandwidth Ranging from b=0.5 to 2.5

The results shown in Figure 31 (a)-(e) with bandwidth changes from b=0.5 to 2.5. Segmented image result in figure (h) at bandwidth 1.5 is best because its segmented area is better.

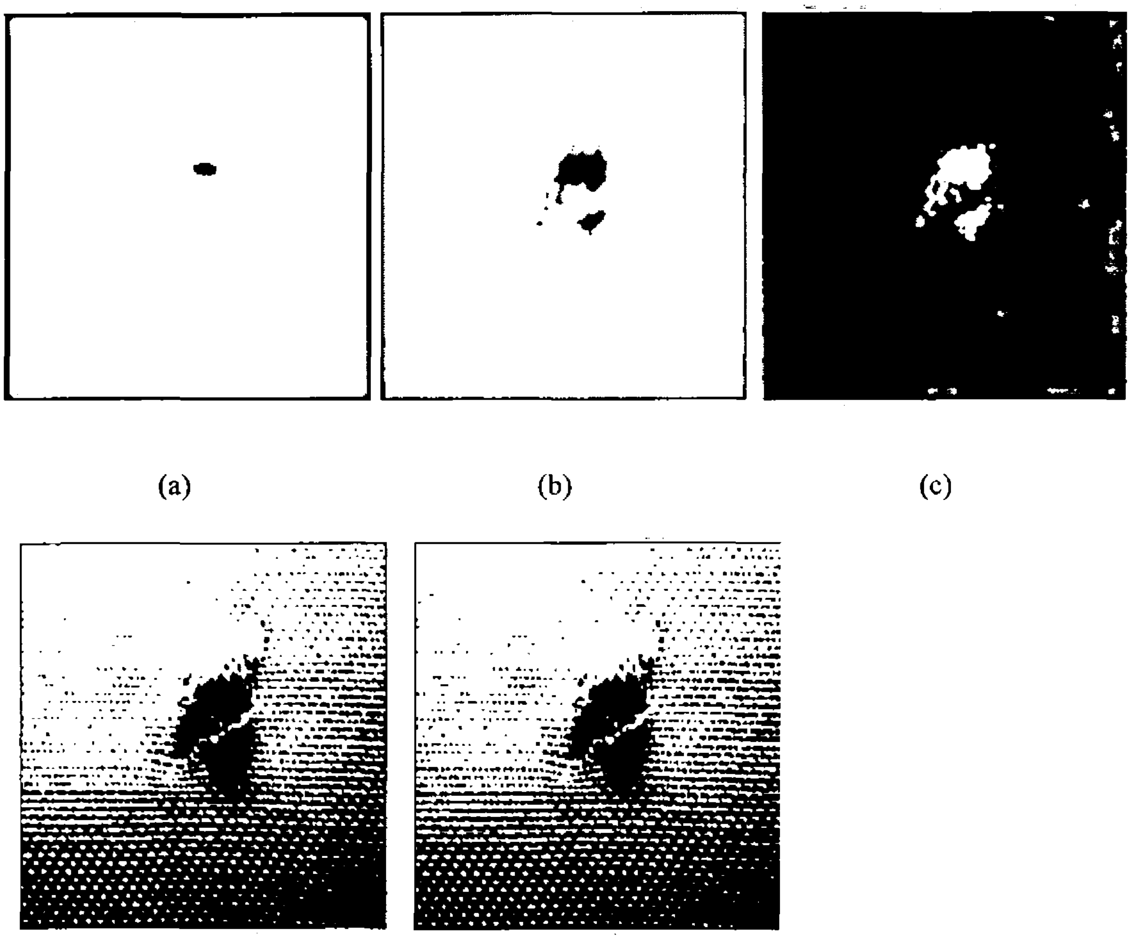
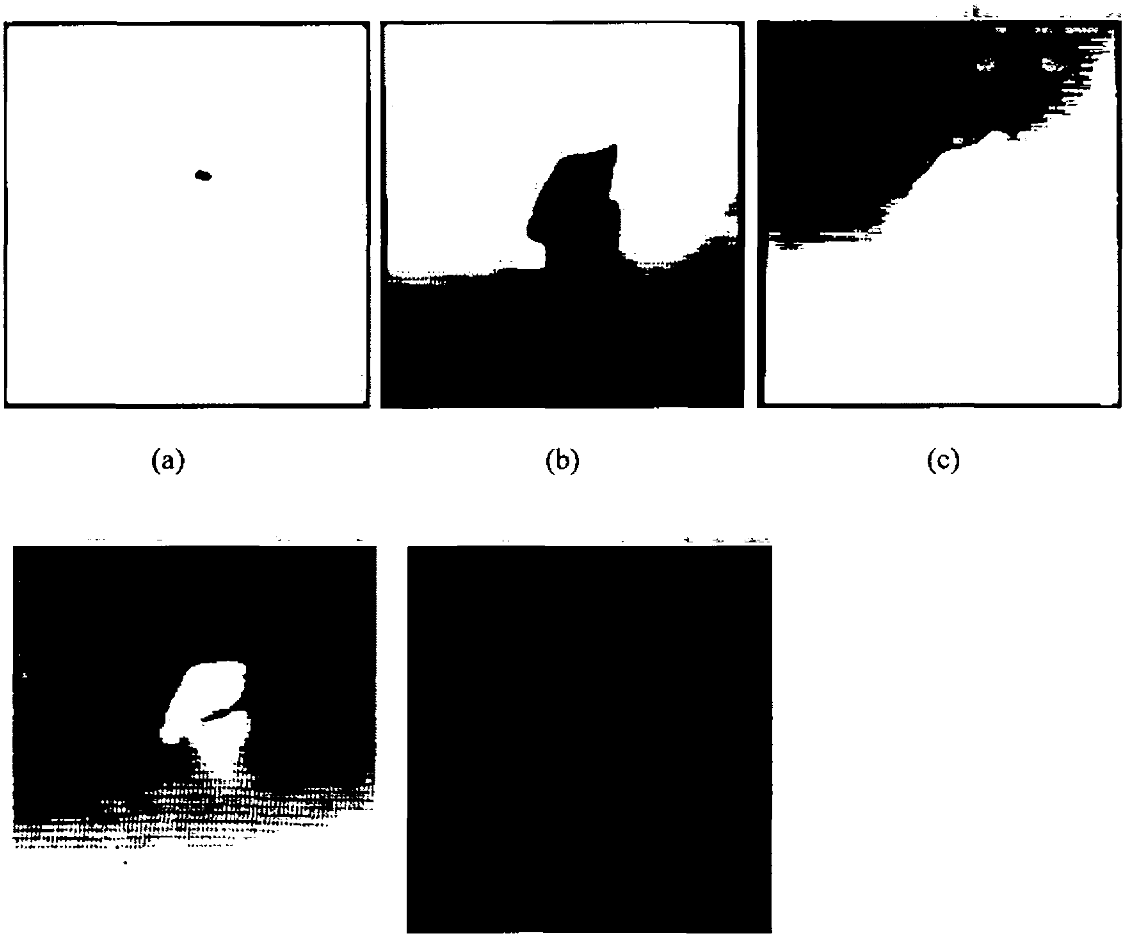


Figure 31: Segmented Results of plain cotton Image with different parameters f=0.5, k=2, γ =0.5 with bandwidth changes (a) b=0.5 (b) b=1 (c) b=1.5 (d) b=2 (e) b=2.5

6.3.6 Segmented Results for Plain Cotton Image Using Gabor Filter with Bandwidth Ranging from $\gamma = 0.5$ to 2.5

The results shown in Figure 32 are about segmentation with gamma changes from $\gamma = 0.5$ to 2.5. Results show poor performance because segmented area in all images is poor. The result shows poor performance.



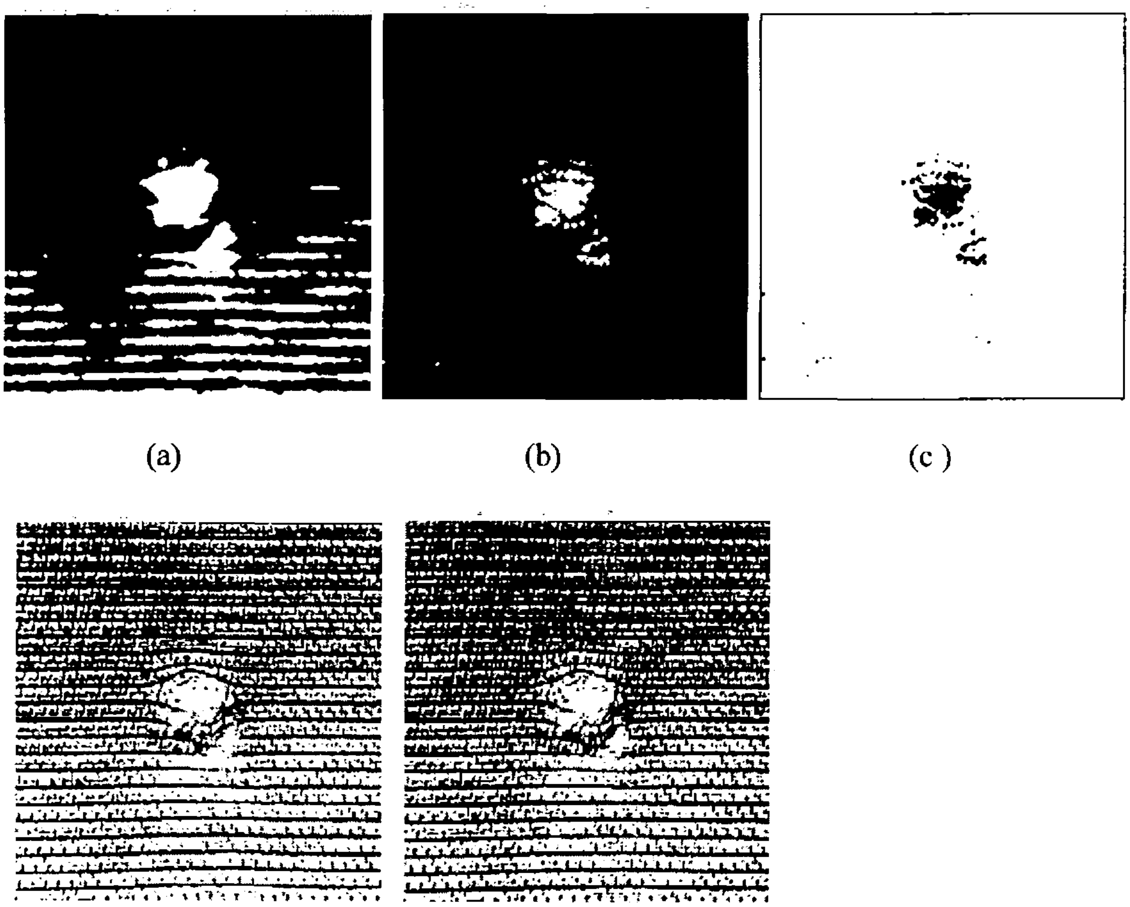
(a) (b) (c)

(d) (e)

Figure 32: Segmented Results of plain cotton Image with gamma changes(a) $\gamma=0.5$ (b)$\gamma=1$ (c) $\gamma=1.5$ (d) $\gamma=2$ (e) $\gamma=2.5$

6.3.7 Segmented Results for Cotton Image Using Gabor Filter with Frequency Ranging fromf=0.5 to 2.5

In Figure 33 results with frequency changes from f=0.5 to f=2.5 are shown. With increase in frequency the segmentation results are poor. At f=1 and f=1.5 good segmentation results are achieved.



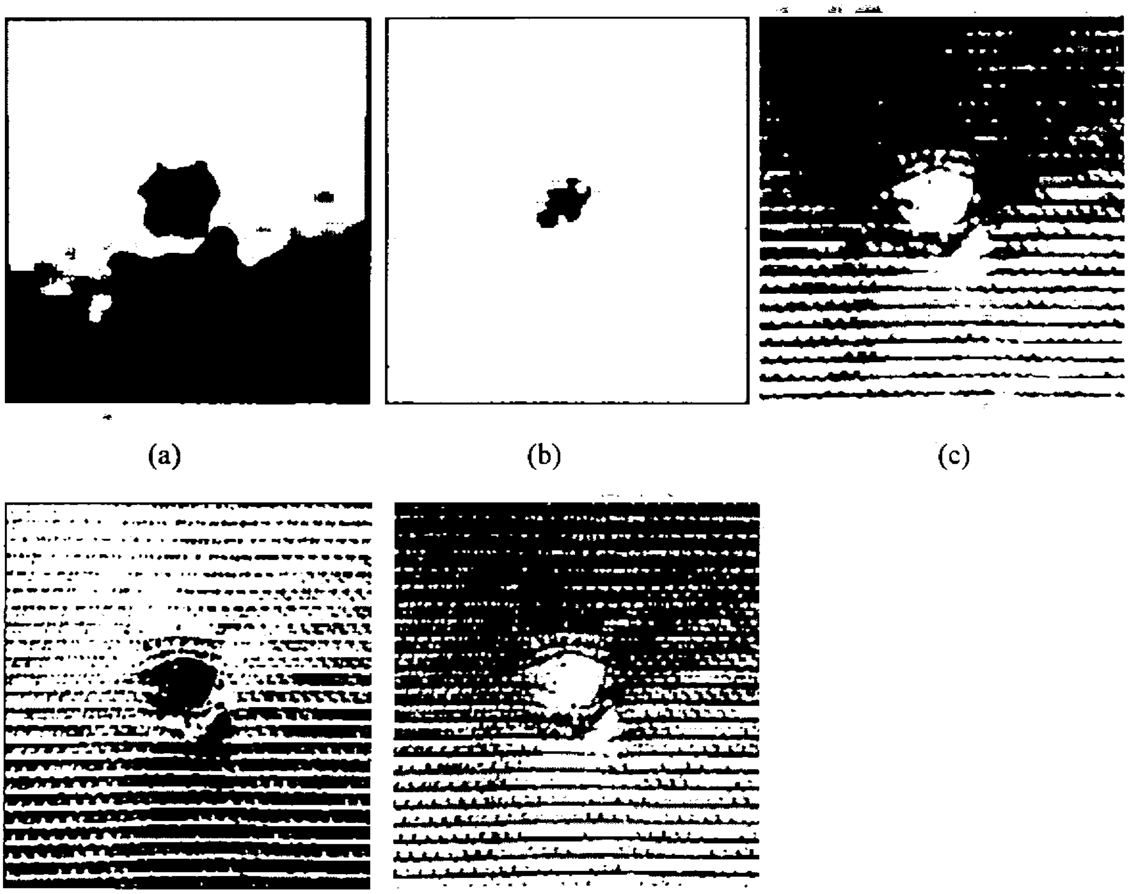
(a) (b) (c)

(d) (e)

Figure 33: Segmented Results of cotton Image with frequency changes from (a) f=0.5 (b) f=1 (c) f=1.5 (d) f=2 (e) f=2.

6.3.8 Segmented Results for Cotton Image Using Gabor Filter with Bandwidth Ranging from b=0.5 to 2.5

Results given below in Figure 34 (a)-(e) with bandwidth changes from b=0.5 to b=2.5 by keeping frequency and gamma constant. Satisfactory results can be achieved at b=1 in figure (g) because its segmented area is better as compare to other results



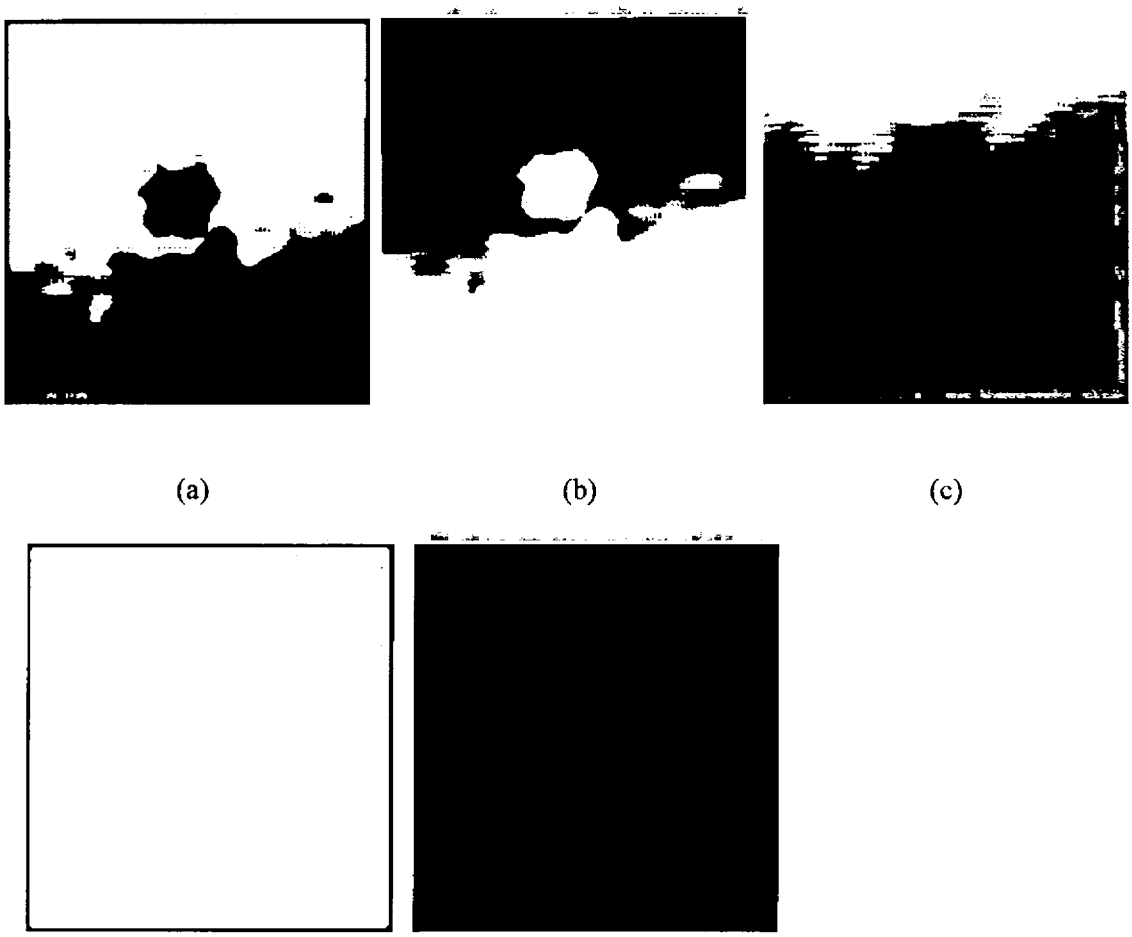
(a) (b) (c)

(d) (e)

Figure 34: Segmented Results of cotton Image with bandwidth changes from (a) b=0.5 (b) b=1 (c) b=1.5 (d) b=2 (e) b=2.5

6.3.9 Segmented Results for Cotton Image Using Gabor Filter with Gamma Ranging from γ =0.5 to 2.5

The Results have shown in Figure 35 (a)-(e) with gamma changes from γ =0.5 to 2.5. Poor segmentation are achieved by changing gamma and none of them shows good performance.



(a) (b) (c)

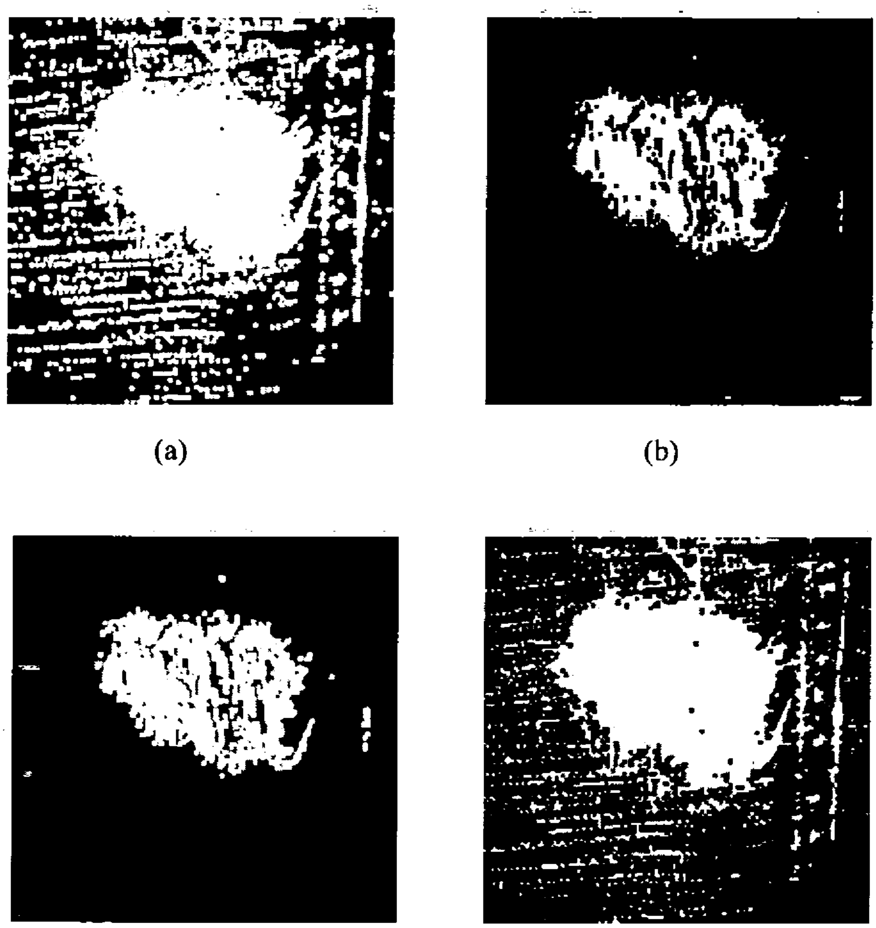
(d) (e)

Figure 35: Segmented Results of cotton Image with gamma changes from (a) γ=0.5 (b) γ=1 (c) γ=1.5 (d) γ=2 (e) γ=2.

6.4 Results for Morphology using different operations

6.4.1 Morphological Results for Jeans Image Using Different Operations

In figure 36 (a)-(d) results have shown for segmented images. The segmentation has done using morphology operations. The defective segmented area for eroded image in Figure 29 at (b) gives best result because its segmented area is better than other when compare with original image defective area.



(a) (b)

(c) (d)

Figure 36:(a) dilation (b) erosion (c) opening (d) closing

6.4.2 Morphological Results of Plain Cotton Image Using Different Operations

The results of image segmentation using morphology have shown in Figure 37. Results are best for eroded image shown in Figure 37 (b) because its segmented area (Black pixels) is better than other segmented images results

(a)

(b)

(c)

(d)

Figure 37: (a) dilation (b) erosion (c) opening (d) closing

6.4.3 Morphological Results of Cotton Image Using Different Operations

In Figure 38 segmented results of plain cotton image using different morphological operations have shown. The eroded image shown in Figure 38 (b) is the best result because its defective segmented area (black pixels) is better.

(a)

(b)

(b)

(c)

(d)

Figure 38 : (a) dilation (b) erosion (c) opening (d) closing

6.5 Statistical Parameters for Evaluation of Segmented Images

(a) Statistical Parameters Evaluation for (Gabor Filter) Results

The table1 shows the statistical parameters for the evaluation of segmented image for Gabor filter and edge detection segmented results

Table 1: Jean image with fabric defect detection using Gabor filter with different statistical parameters (a) f=0.5 to 2.5, b=1, γ=0.5(b) b=0.5 to 2.5, γ=0.5, f=0.5(c)γ =0.5 to 2.5,f=0.5 and b=0.5

(a) f=0.5 to 2.5, b=1,γ= 0.5

Frequency	Mean =μ	SD=σ	Root mean square	Entropy
0.5	55.2614	100.0497	114.2968	2.5912
1	63.4826	101.9914	120.1344	3.9242
1.5	189.7406	103.0862	215.9357	4.0589
2	86.3121	98.5154	130.97741	6.2880
2.5	76.7928	99.6562	125.8113	4.9767

(b) b=0.5 to 2.5, γ=0.5, f=0.5

Bandwidth	Mean =μ	SD=σ	Root mean square	Entropy
0.5	53.9689	99.6369	113.3145	2.1708
1	56.4066	100.8666	115.5672	2.4848
1.5	186.6621	108.1182	215.7134	3.1105
2	197.0972	99.3848	220.7366	3.7079
2.5	190.4551	103.7459	216.8787	3.7803

(c)γ =0.5 to 2.5,f=0.5, b=0.5

Gamma	Mean =μ	SD=σ	Root mean square	Entropy
0.5	189.8702	107.6288	218.2536	2.4514
1	54.0259	99.6713	113.3718	2.1779
1.5	44.7045	92.0109	102.2962	2.2825
2	63.6382	105.8162	123.4783	2.4015
2.5	252.6666	0.9442	252.6684	2.9426

In Table 1 results have shown for different parameters like (mean, SD, rms, entropy). The best result for jeans image is at b=0.5 with entropy 2.1708

Table 2: Plain cotton image with fabric defect detection using Gabor filter with different statistical parameters (a) f=0.5 to 2.5, b=1,γ=0.5(b) b=0.5 to 2.5, γ=0.5, f=0.5(c) γ =0.5 to 2.5,f=0.5 and b=0.5

(a) f=0.5 to 2.5, b=1, γ= 0.5

Frequency	Mean =μ	SD=σ	Root mean square	Entropy
0.5	250.5095	22.4186	251.5107	1.6709
1	248.8472	36.6303	251.5287	1.5387
1.5	248.8451	36.6213	251.5253	1.5408
2	248.7796	36.6921	251.47092	1.5611
2.5	143.0064	88.6260	168.2422	7.5296

(b) b=0.5 to 2.5, γ=0.5, f=0.5

Bandwidth	Mean =μ	SD=σ	Root mean square	Entropy
0.5	252.2177	9.8692	252.4107	1.4748
1	248.6713	30.1346	250.4906	1.4971
1.5	8.7875	35.05187	36.1366	1.3887
2	151.1801	112.2015	188.2674	4.7914
2.5	148.3626	114.2525	187.2567	4.5183

(c) b=0.5 to 2.5, γ=0.5, f=0.5

Gamma	Mean =μ	SD=σ	Root mean square	Entropy
0.5	252.4054	7.5301	252.5177	1.9662
1	143.4539	122.7358	188.7938	2.5954
1.5	155.6196	120.3587	196.7326	2.5787
2	0.0000	0.0000	0.0000	0
2.5	89.6344	114.2009	145.1764	3.5047

In table 2 results have shown for statistical parameters evaluation of different segmented images. The result at b=1.5 with entropy is 1.3887 which points out best segmented result

Table 3: Cotton image with fabric defect detection using Gabor filter with different statistical parameters (a) f=0.5 to 2.5, b=1,γ= 0.5(b) b=0.5 to 2.5, γ=0.5, f=0.5(c)γ =0.5 to 2.5,f=0.5 and b=0.5

(a) f=0.5 to 2.5, b=1, γ= 0.5

Frequency	Mean =μ	SD=σ	Root mean square	Entropy
0.5	39.8494	82.0678	91.2311	3.5431
1	7.7185	30.5339	31.4944	1.0316
1.5	250.3544	31.4575	252.3230	1.1016
2	122.5004	99.2900	157.6860	6.9917
2.5	105.6177	99.7335	145.2649	6.7709

(b) b=0.5 to 2.5, γ=0.5, f=0.5

Bandwidth	Mean =μ	SD=σ	Root mean square	Entropy
0.5	144.8737	122.3395	189.6190	2.7487
1	249.8961	25.4372	251.1874	1.1427
1.5	89.2548	110.2652	141.8621	4.9742
2	145.0368	110.8710	182.5597	5.9247
2.5	100.5680	108.7401	148.1160	5.8805

(c) γ=0.5 to 2.5, f=0.5, b=0.5

Gamma	Mean =μ	SD=σ	Root mean square	Entropy
0.5	143.2137	122.4879	188.4502	2.8318
1	123.2915	123.6484	174.6131	2.6297
1.5	73.1656	110.8154	132.7903	2.3588
2	0.0000	0.0000	0.0000	0
2.5	252.6676	0.9559	252.6694	1.1172

In table 3 the result are given for statistical parameters evaluation of segmented images.

The value at f=1 at entropy 1.0316 is best.

(b) Statistical Parameters Evaluation for (Morphology) Results

Table 4: Statistical parameters evaluation for jeans image using morphology operations

Operators	Mean	SD	RMS	Entropy
Dilation	26.70405579	28.37540147	38.96498434	2.7864
Erosion	6.24278259	17.60227858	18.67652392	0.9846
Opening	8.49736023	20.54737610	22.23510278	1.0686
Closing	17.88905334	26.48877242	31.96362455	2.0870

In table 4 results have shown for different statistical parameters, evaluation mean, SD, rms and entropy for different morphological operations. The erosion with entropy 0.9846 is best.

Table 5: Statistical parameters evaluation for plain cotton image using morphology operations

Operators	Mean	SD	RMS	Entropy
Dilation	58.70379639	3.83510225	58.82893607	0.0852
Erosion	61.60899353	8.70640074	62.22113385	0.2819
Opening	62.13200378	6.82123535	62.50532094	0.1983
Closing	27.84042358	2.35512587	27.93986047	0.1112

In table 5 results for different statistical parameters like (mean, SD, rms and Entropy) have shown. The erosion at entropy is 0.2819 which points out be that the segmentation result at erosion operation is best.

Table 6: Statistical parameters evaluation for cotton image using morphology operations

Operators	Mean	SD	RMS	Entropy
Dilation	43.91520691	1.69547362	43.94792405	0.0421
Erosion	62.02449036	7.25644129	62.44752472	0.2177
Opening	106.85969543	9.69080943	107.29821199	0.2147
Closing	85.65032959	4.77663775	85.78342047	0.0965

The table 6 is about result of statistical parameters evaluation of morphology operations.

The result at erosion with entropy 0.2177 performs best instead of all other results.

6.6 Evaluating Black and White Pixels in Images

(a) Measure Black and White Pixels for Gabor Filter Results

Table 7: Calculate black and white pixels value in Plain cotton image (a) f=0.5 to 2.5, b=1, γ=0.5 (b) b=0.5 to 2.5, γ=0.5, f=0.5 (c) γ =0.5 to 2.5,f=0.5, b=0.5

(a) f=0.5 to 2.5, b=1, γ=0 .5

Frequency	Original gray scale area	Total no of pixels	Black pixels & %black pixels	White pixels & %white pixels
0.5	65536	65536	51794,79.1%	13742,20.9%
1	65536	65536	48621,74.2%	`16915,25.8%
1.5	65536	65536	14283,21.8%	51253,78.2%
2	65536	65536	37275,56.9%	28261,43.1%
2.5	65536	65536	46366,71.0%	18908,29.0%

(b) b=0.5 to 2.5, γ=0.5, f=0.5

Bandwidth	Original gray scale area	Total no of pixels	Black pixels & %black pixels	White pixels & %white pixels
0.5	65536	65536	52638,80.3%	12898,19.7%
1	65536	65536	51448,78.5%	14088,21.5%
1.5	65536	65536	16624,25.4%	14088,74.6%
2	65536	65536	14606,22.3%	50930,77.7%
2.5	65536	65536	12829,19.6%	52707,70.4%

(c) γ =0.5 to 2.5, f=0.5 , b=0.5

Gamma	Original gray scale area	Total no of pixels	Black pixels & %black pixels	White pixels & %white pixels
0.5	65536	65536	16548,25.3%	48988,74.7%
1	65536	65536	52089,79.5%	13447,20.5%
1.5	65536	65536	54753,83.5%	10783,16.5%
2	65536	65536	49854,76.1%	15682,23.9%
2.5	65536	65536	2284,3.5%	63252,96.5%

The table7 is about results for total number of pixels, black and white pixels in image separately for different segmented images results at different parameter.

Table 8: Calculate black and white pixels value in Plain cotton image (a) f=0.5 to 2.5, b=1, γ=0.5 (b) b=0.5 to 2.5, γ=0.5, f=0.5 (c) γ =0.5 to 2.5, f=0.5, b=0.5

(a) f=0.5 to 2.5, b=1, γ=0 .5

Frequency	Original gray scale area	Total no of pixels	Black pixels & %black pixels	White pixels & %white pixels
0.5	65536	65536	1964,3.0%	63572,97.0%
1	65536	65536	2494,3.8%	63042,96.2%
1.5	65536	65536	2491,3.8%	63045,96.2%
2	65536	65536	13780,21.0%	51756,79.0%
2.5	65536	65536	31170,47.6%	34366,52.4%

(b) b=0.5 to 2.5, γ=0.5, f=0.5

Bandwidth	Original gray scale area	Total no of pixels	Black pixels & %black pixels	White pixels & %white pixels
0.5	65536	65536	3135,4.8%	34182,95.2%
1	65536	65536	2472,3.8%	63064,96.2%
1.5	65536	65536	63697,97.2%	1839,2.8%
2	65536	65536	27972,42.5%	37564,57.5%
2.5	65536	65536	27333,42.2%	38203,57.8%

(c) γ =0.5 to 2.5,f=0.5, b=0.5

Gamma	Original gray scale area	Total no of pixels	Black pixels & %black pixels	White pixels & %white pixels
0.5	65536	65536	2835,4.3%	62701,95.7%
1	65536	65536	29610,45.2%	35926,54.8%
1.5	65536	65536	26700,40.7%	38836,59.3%
2	65536	65536	56628,100.0%	0,0.0%
2.5	65536	65536	41146,62.8%	24390,31.2%

In table 8 is about results of pixels calculation of different segmented images results of plain cotton image

Table 9: Cotton image with fabric defect (a) f=0.5 to 2.5, b=1, γ=0.5 (b) b=0.5 to 2.5, γ=0.5, f=0.5 (c) γ =0.5 to 2.5,f=0.5, b=0.5

(a) f=0.5 to 2.5, b=1, γ= 0.5

Frequency	Original gray scale area	Total no of pixels	Black pixels & %black pixels	White pixels & %white pixels
0.5	65536	65536	52150,79.6%	13386,20.4%
1	65536	65536	64045,97.7%	1491,2.3%
1.5	65536	65536	2152,3.3%	63384,96.7%
2	65536	65536	28477,43.5%	37059,56.5%
2.5	65536	65536	20156,30.8%	45380,69.1%

(b) b=0.5 to 2.5, γ=0.5, f=0.5

Bandwidth	Original gray scale area	Total no of pixels	Black pixels & %black pixels	White pixels & %white pixels
0.5	65536	65536	28784,43.9%	36752,56.1%
1	65536	65536	2180,3.3%	63356,96.7%
1.5	65536	65536	37885,57.8%	27651,42.2%
2	65536	65536	25378,38.7%	40158,61.3%
2.5	65536	65536	31734,48.4%	33802,51.6%

(c) γ=0.5 to 2.5, f=0.5, b=0.5

Gamma	original gray scale area	Total no of pixels	Black pixels & %black pixels	White pixels & %white pixels
0.5	65536	65536	29233,44.6%	36303,55.4%
1	65536	65536	33529,51.2%	32007,49.8%
1.5	65536	65536	46397,70.8%	19139,29.2%
2	65536	65536	55216,100.0%	0,0.0%
2.5	65536	65536	2292,3.5%	64244,96.5%

Table 9 have shown results of pixels value for plain cotton image (Segmented results).

(b) Measure Black and White Pixels for Morphological Operations

Table 10: Calculate area of binary image, black and white pixels value in Jeans image for morphology operations

Operators	Original gray scale area	Total no of pixels	Black pixels,% black pixels	white pixels,% white pixels
Dilation	65536	65536	30370, 46.3%	35166, 53.7%
Erosion	65536	65536	57158, 87.2%	8378, 12.8%
Opening	65536	65536	54873, 83.7%	10663, 16.3%
Closing	65536	65536	42500, 64.8%	23036, 35.2%

In table 10 is about results of total number of pixels, black and white pixels for morphological operations.

Table 11: Calculate area of binary image, black and white pixels value in plain cotton image for morphology operations

Operators	Original gray scale area	Total no of pixels	Black pixels,% black pixels	white pixels,% white pixels
Dilation	65536	65536	194, 0.3%	65342, 0.97%
Erosion	65536	65536	1002, 1.5%	64534, 98.5%
Opening	65536	65536	577, 0.9%	64959, 99.1%
Closing	65536	65536	389, 0.6%	65147, 99.4%

In table 11 have shown results of pixels calculations for different morphology operations

Table 12: Calculate black and white pixels in Cotton image for morphology operations

Operators	Original gray scale area	Total no of pixels	Black pixels,% black pixels	white pixels,% white pixels
dilation	65536	65536	47, 0.1%	65489, 0.99%
erosion	65536	65536	671, 1.0%	64866, 99.0%
opening	65536	65536	323, 0.5%	65213, 0.95%
closing	65536	65536	120, 0.2%	65416, 0.98%

In table 12 pixels calculation results have shown for different morphology operations.

6.7Area Measurement of Segmented Images

(a) Area Measurement for Gabor Filter Segmented Images

Table 13: Jeans image with effective area measurement before and after segmentation (a) freq=0.5 to 2.5(b) b=0.5 to 2.5(c) γ=0.5 to 2.5

(a) f=0.5 to 2.5

frequency	Original image defected area in pixels	Segmented image defected area in pixels	Effective Area =SI/OI
0.5	12250	14742	1.2218
1	12250	16915	1.3810
1.5	12250	14283	1.2660
2	12250	28261	2.3071
2.5	12250	18908	1.5435

(b) b=0.5 to 2.5

Bandwidth	Original image defected area in pixels	Segmented image defected area in pixels	Effective Area=SI/OI
0.5	12250	13742	1.1217
1	12250	16915	1.3801
1.5	12250	14283	1.2660
2	12250	28261	2.3071
2.5	12250	18908	1.5435

(c) γ=0.5 to 2.5

gamma	Original image defected area in pixels	Segmented image defected area in pixels	Effective Area =SI/OI
0.5	12250	16548	1.3508
1	12250	13647	1.2301
1.5	12250	10783	1.8802
2	12250	15800	1.2897
2.5	12250	22840	1.8644

In table 13 results have shown about effective area measurement of proposed method results at different parameters (frequency, gamma and bandwidth).The effective area at b=0.5 is 1.1217 best. Effective area can be measured by dividing segmented area by original image defective area.

Table 14: Plain cotton image with effective area measurement before and after segmentation (a) freq=0.5 to 2.5(b) b=0.5 to 2.5(c) γ=0.5 to 2.5

(a) f=0.5 to 2.5

frequency	Original image defected area in pixels	Segmented image defected area in pixels	Effective Area=SI/OI
0.5	3893	1964	0.5045
1	3893	2494	0.6406
1.5	3893	2491	0.6398
2	3893	13780	3.5396
2.5	3893	31170	8.0066

(b) b=0.5 to 2.5

Bandwidth	Original image defected area in pixels	Segmented image defected area in pixels	Effective Area =SI/OI
0.5	3893	3135	0.8053
1	3893	2472	0.6349
1.5	3893	1839	0.4724
2	3893	27972	7.1852
2.5	3893	27333	7.0211

(c) γ=0.5 to 2.5

Gamma	Original image defected area in pixels	Segmented image defected area in pixels	Effective Area=SI/OI
0.5	3893	2835	0.7283
1	3893	29610	7.6059
1.5	3893	26700	6.8585
2	3893	65536	16.8343
2.5	3893	41146	10.5693

In table 14 effective area have shown for different parametric results. The effective area for plain cotton image at parameter b=1.5 is 0.4724 which is best.

Table 15: Cotton image with effective area measurement before and after segmentation (a) freq=0.5 to 2.5(b) b=0.5 to 2.5(c) γ=0.5 to 2.5

(a) f=0.5 to 2.5

Frequency	Original image defected area in pixels	Segmented image defected area in pixels	Effective Area =SI/OI
0.5	3306	13386	4.0491
1	3306	1491	0.4510
1.5	3306	2152	0.6510
2	3306	37059	11.2096
2.5	3306	45380	13.7265

(b) b=0.5 to 2.5

Bandwidth	Original image defected area in pixels	Segmented image defected area in pixels	Effective Area=SI/OI
0.5	3306	28784	8.7065
1	3306	2180	0.6594
1.5	3306	27651	8.3638
2	3306	25378	7.6764
2.5	3306	33802	10.2244

(c) γ=0.5 to 2.5

gamma	Original image defected area in pixels	Segmented image defected area in pixels	Effective Area =SI/OI
0.5	3306	29233	8.8424
1	3306	32007	9.6815
1.5	3306	19139	5.7892
2	3306	55216	16.7021
2.5	3306	64244	19.4325

Effective area can be measured for different parameters of proposed method in table 15. The effect area at parameter f=1 is 0.4510 which is best amongst other results.

Table 16: Jeans image with effective area measurement before and after Segmentation using morphological operations

Operators	Original image defected area in pixels	Segmented image defected area in pixels	Effective Area =SI/OI
Dilation	12250	35166	2.8707
Erosion	12250	8378	0.6839
Opening	12250	10663	0.8705
Closing	12250	23036	1.8805

In table 16 effective area measurement results of morphology operations have shown. The effective area at erosion 0.6839 is best.

Table 17: Plain cotton image with area effective area measurement before and after segmentation using morphological operations

Operators	Original image defected area in pixels	Segmented image defected area in pixels	Effective Area =SI/OI
Dilation	3893	194	0.0498
Erosion	3893	1002	0.2574
Opening	3893	577	0.1482
Closing	3893	389	0.0999

In table 17 effective area have shown for different morphology operations and the effective area at erosion is 0.2574 which is best area as compare to others.

(b)Area Measurement for Morphology Based Segmented Result

In table 18 effective area have shown for different morphology operations results out of which erosion with effective area 0.2029 is best.

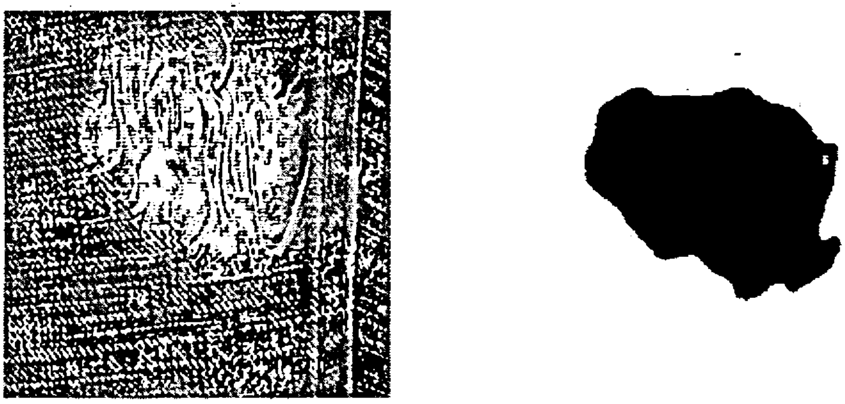
Table 18: Cotton image with effective area measurement before and after segmentation using morphological operations

Operators	Original image defected area in pixels	Segmented image defected area in pixels	Effective Area =SI/OI
Dilation	3306	47	0.0142
Erosion	3306	671	0.2029
Opening	3306	323	0.0977
Closing	3306	120	0.0363

6.8 Original Image and Best Segmented Result

6.8.1 Original Jeans Image and Best Result At b=0.5

Figure 39 shows original gray scale and best segmented results of proposed method

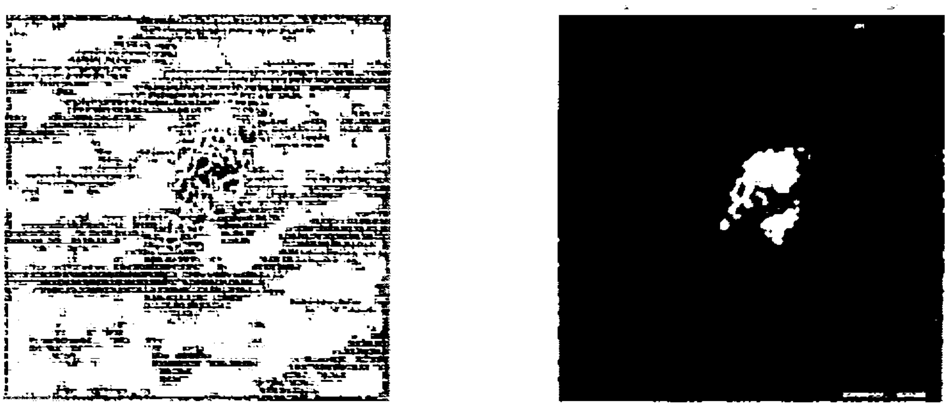


(a) Original jeans image (b) After defect detection

Figure 39: (a) Original jean gray scale image (b) After defect detection

6.8.2 Original plain cotton image and best result at results at b=1.5

Figure 40 shows original gray scale plain cotton image and best segmented image after apply proposed method



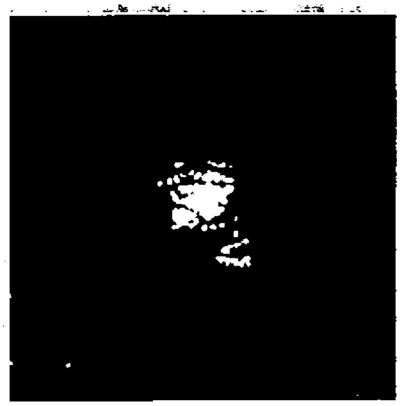
(a) Original plain cotton image (b) After defect detection

Figure 40: (a) Original plain Cotton Image (b) After defect detection

6.8.3 Original plain cotton image and best result at f=1

Figure 41 shows original gray scale cotton image and best segmented image result of proposed method

(a) Original cotton image



(b) After defect detection

Figure 41: (a) Original Cotton Image (b) After defect detection

6.9 Better Segmented Results for Morphological Operations

(a)

(b)

(c)

Figure 42: Better segmented results using morphological operations (a) for jeans image (b) for plain cotton image (c) for cotton image

6.12 Effective Area Comparison between Proposed Method and Morphology Technique

Area comparisons of proposed method and morphology results have shown in figure below. In the results greater the effective area better will be the result because when defective segmented area is close to original image defective area the error is low and good. Gabor filter effective area is much better than edge detection area. In the graph shown below vertical axis represents area and horizontal axis represents algorithms used in research.

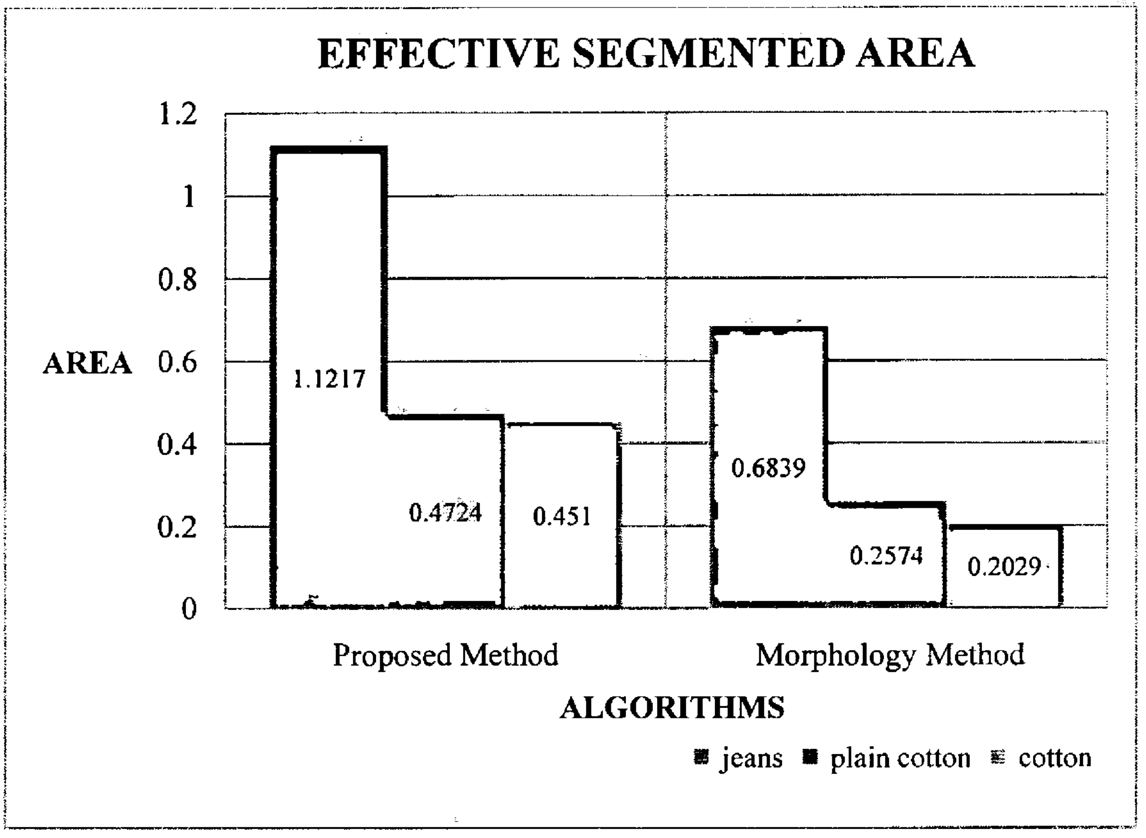


Figure 43: Effective area comparison

CHAPTER 8

CONCLUSION AND FUTURE WORK

This chapter comprises of conclusion and future work

8.1 Conclusion

The research work presented in this thesis is about performance of Gabor filter's for segmentation of defective area in fabric textures images. The 2-D Gabor filter optimality localizes in both space and frequency domain. Furthermore we have compared the results of Gabor filter and morphological technique. At the end performance of segmented images has been checked by means of statistical parameters like (mean, SD, rms, entropy and area) and techniques that are used in the research work. Experimental results show that with optimal setting of parameters the Gabor filter performs better than other techniques.

8.2 Future work

The application of Gabor filters has been growing at a very fast rate. Gabor filters can be used for image segmentation, weed image classification, Palm print recognition, Texture segmentation, for the illumination invariant recognition of color texture, for an automatic inspection system for textile images. We use Gabor filter for automatic visual inspection in textile industry in which camera is attached with PC. When cotton roll move than camera move on the roll of the cloth and detect defect and send this information to pc and then pc measures and calculate the defective area and other properties related to that fabric defect.

Moreover for future work we can use various techniques like Radon neural network, Fuzzy, Adaptive and GA in order to attain the best output without performing calculations for each and every combination. This work can be done by using this technique will lead to more efficiency and less tedious work.

The 2-D Gabor filter after some modifications will change into 3-D which is hot topic these days in the field of research. This method is also fruit full in other defect detection fields like tumor detection, iris detection, finger print detection, license plate detection etc.

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