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GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES

FABRIC DEFECT DETECTION USING IMAGE PROCESSING TECHNIQUES

by
Savaş BAĞKUR

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İZMİR

FABRIC DEFECT DETECTION USING IMAGE PROCESSING TECHNIQUES

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Savaş BAĞKUR

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M.Sc THESIS EXAMINATION RESULT FORM

We have read the thesis entitled **"FABRİC DEFECT DETECTION USING IMAGE PROCESSING TECHNIQUES"** completed by **SAVAŞ BAĞKUR** under supervision of **ASST. PROF. DR. YAVUZ ŞENOL** and we certify that in our opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Science.

Asst. Prof. Dr. Yavuz Şenol

Supervisor

Prof. Dr. Ender Kuyan

(Jury Member)

Yrd. Doç. Dr. Haldun Samel

(Jury Member)

Prof. Dr. Mustafa SABUNCU

Director

Graduate School of Natural and Applied Sciences

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ABSTRACT

The aim of this thesis is to design a defect detection system using image processing techniques. Inspection process is very important for textile industry. Defects decrease the profits of manufacturersand cause undesirable loses. Therefore, to reduce loses manufactures initially started to employ experts to detect the currently available defects on the fabrics. However, human experts have some drawbacks such as tiredness, boredom, and inattentiveness which cause to reduce the detection of faults. Because of that reason, textile industry started to develop new methods. Fortunately, the computer vision technologies with new developments in software and hardware have been applied to textile industry to increase the effectiveness of defect detection system.

In our work, Difference of offset Gaussian (DOOG) filter has been used as the main part of fabric defect detection system. So far DOOG filter have not been used in textile defect detection systems. But, it was used for analysing the textures.Fabric patterns have symmetric and regular structures and whereas the defects disrupt the regularity. It is suitable condition to apply DOOG filters to images. DOOG filter is easily understandable and have simple structure. The system first transfers the filter and image in frequency domain then calculate the convolution of them. After this, filtered image convert back to time domain and the results can give information about the defects. In addition to DOOG filter, histogram analysis and thresholding is used to increase the detection of faults.

In finding the faults and testing the system performance real fabric images are used. This provided a real test to the detection system. The results have shown that all of the defects have been correctly identified.

Keywords: Automatic Fabric defect detection system, difference of offset Gaussian (DOOG) filter, pattern recognition, spatial filtering approach.

GÖRÜNTÜ İŞLEME TEKNİKLERİ İLE KUMAŞ DOKUMA HATALARININ TESPİTİ

ÖZ

Bu tezin amacı görüntü işleme tekniklerinin kullanarak kumaş hatası algılama sistemi tasarlamaktır. Hata algılama işlemi tekstil endüstrisinde önemli bir yer tutar. Kumaş hatalar, üreticiler için istenmeyen kayıplara ve üretim karının azalmasına sebep olur. Bu nedenle, hatalı ürün üretimini azaltmak için, kumaş kontrol uzmanları kullanılmıştır. Ancak uzmanlar, yorgunluk, bıkkınlık ve dikkatsizlik gibi insani durumlardan sıkça etkilenmesi hataları algılama yüzdelerini düşürür. Bu gibi sebeplerden dolayı tekstil endüstrisi yeni metotlar geliştirmeye başladı. Bilgisayar görüntüleme sistemleri, yazılım ve donanımdaki yeni gelişmeler tekstil endüstrisinde hata algılama sistemlerinin etkililiğini arttırmak ve geliştirmekte kullanıldı.

Bu çalışmada, DOOG filtreleri, fabrika kumaş hatası algılama sisteminin ana parçası olarak kullanıldı. DOOG filtreleri şimdiye kadar, tekstil hata tespit sistemlerinde kullanılmadı fakat dokuların analizinde başarılı sonuçlar vermiştir. Kumaşlar simetrik ve düzenli bir yapıya sahiptirler, hatalar ise bu düzenliliği bozan yapılardır. Kumaşların bu yapısından dolayı, DOOG filtrelerini kumaşlar ile yapılan çalışmalarda iyi sonuçlar verir. DOOG filtresi kolayca anlaşılabilir ve basit bir yapıya sahiptir. Tasarlanan sistem, filtreleri resimlere uygularken önce filtreleri ve kumaş resmini frekans uzayına çevirip konvolusyon işlemini gerçekleştirdikten sonra tekrar zaman uzayına çevirerek işlemi tamamlar. Bu aşamadan sonra hatalı alanlar hakkında bilgiler elde ederiz. Bu bilgileri daha da belirleyici hale getirmek için, histogram analizi ve eşikleme işlemleri kullanılır.

Hataların bulunmasında ve sistem performansını test ederken gerçek kumaşlar kullanılmıştır. Bu da kumaş hataları algılama sistemini daha başarılı şekilde test edebilmemizi sağlamıştır. Sonuçlar bütün kumaş hatalarının doğru olarak tanımlanabildiğini göstermektedir.

Anahtar sözcükler: Otomatik Kumaş hatası algılama sistemleri, DOOG filtresi, örüntü tanıma, uzaysal filtreleme yöntemi.

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CHAPTER ONE
INTRODUCTION

1.1 Background of Fabric Defect Inspection Systems

Around seven cover billion people are currently live on in the world and all the people use clothes to their bodies. Therefore, textile industry becomes very large and an important sector. Fabrics are the raw materials of textile industry and they have very sensitive structure. Consequently, quality is very important parameter for textile, so good quality products is a key issue for increasing rate of profit and customer satisfaction (Schneiderman A. M, 1986), as a result the industry’s competitive edge is expanded in the global market (K. Srinivasan, P. H. Dastor, P. Radhakrishnaihan and S. Jayaraman, 1992). If defects in the fabrics are not discovered before the garment manufacturing process, significant financial losses can adversely affectsbothdealersandmanufacturers. For example, if damages in patterns of the fabric are, due to human absence, not discovered prior to manufacturing the fabric, as a result considerable loss of time, money and distrust between dealersandmanufacturers can occur. In addition, defected fabrics lose 55 − 65% value against non-defected fabrics (K. Srinivasan, P. H. Dastor, P. Radhakrishnaihan and S. Jayaraman, 1992). This is a verygreat loss for manufacturers. For this reason, the inspection of fabric defects is necessary and important for the textile industry.

The demand of Textile industry cause to improvements in weaving machines, looms, etc. In short, a revolution can occur. As a result, the manufacturing, speed of machines, numbers of employee’s rate are immediately increased. However these improvements caused some disruptions and the most important of these disruptions, is the number of increasing errors. Fatigue, megrims and carelessness are some of the conditions by that the inspector performance is easily affected. So, inspection department’s success rate is always lower than expected rates Therefore, automatic inspection systems are designed to prevent or minimize defects’ effects (Chan, C. and Pang, 2000), (Behera B. K, 2009).

The fabric defect causes deterioration on the fabric pattern and there are various pattern faults. The yarns are weaved in the longitudinal direction of the fabric that is named as warp direction. If the yarns are weaved in the width-wise direction they are weft direction. These makes the fabric patterns In general, the defects occur in weaving process and several reasons can cause to defects formations (A. S. Tolba, A. N. Abu-Rezeq, 1997). The most important reason of these defects, such as double-end, double-pick, irregular weft density, broken end, and broken pick, slubs, contaminations or waste can occur if yarns failure in pattern. Furthermore, a large part of defects are related with fabric machine structural failures or machine residue (A. S. Malek, 2012).

In textile industry defect detection process is named as fabric inspection. Next sections will give brief information about fabric inspections, fabric inspections' techniques and also compare these techniques.

1.2. Fabric Inspection

Inspection process is very important for manufacturing industry. Nowadays, importance of inspection process almost equals with manufacturing process in modern industrialism perspective. The aim of inspection process is to identify the occurred errors or defects, if any exist, then to change parameter or give alert to inspector for checking the manufacturing process (Newman T. S. and Jain A.K, 1995). Mainly, fabric defect detection use two type of inspection model (Kumar A, 2008). The first one is the Human based Inspection Systems (HIS).The second system is Automated based Inspection Systems (AIS).

1.2.1Human Based Inspection Systems (HIS)

In modern textile industry, fabrics are available in more complex web form, also advanced machines weave wide and long fabrics as soon as possible. In addition, fabrics easily affected by external factors. Consequently, the inspection process becomes more difficult and more complicated stage (Conci A. and Proença C. B., 2000). Therefore, industrial fabric inspection (Kumar A. and Pang G., 2002) has extremely high requirements.

Traditionally, as its name suggests. Human based Inspection Systems based on human. After manufacturing process, inspection looms are used for controlling the weaved fabrics. There are different types of inspection looms. Same operating principles are used. The principle is a fabric cling from mill to mill. An inspector controls the fabrics as shown in figure (1.1) (Behera B. K., Text. B. and Tech, 2004), (Baykut A., Ozdemir S., Meylani R., Ercil A., Ertuzun A., 1998).

Figure 1.1 Human based inspection systems

When the inspector notices a defect on the moving fabric, then he records the defect and its location. During the inspection process, if the operator encounters with too many defects, the inspector warns the production department for immediate correction of faults. Either the new parameter are entered the weave machine or the production is stopped (Kumar A., 2008), (Dorrity J., Vachtsevanos G. and Jasper W., 1996).

1.2.2 Drawbacks of Visual Fabric Inspection

From the first day that Inspection process is implemented in Textile industry, Human based inspection Systems met all the requirements (Anstey J., Peters D. and Dawson C., 2005). Although manpower is still used in inspection process, while modern weaving machines increase the production rate and production pattern size. So, the human based inspection has no ability to satisfy today requirements because of the limitations based on their physiological nature of human. The researches shows that Human based Inspection Systems detect only 60-70% of the defects (T. S. Newman, and A. K. Jain, 1995). Beside this, Human based Inspection Systems (HIS) suffers from many drawbacks. They can be described as follows:

(1) Training phase takes a long time to teach a good inspector
(2) The inspection becomes difficult and tiresome because of Limitation of human's body even if the best inspectors are available.
(3) Human perceiving speed is slower than machines so manufacturing process becomes longer.
(4) Human inspectors have limited time to focus on, because humans attentions affects by tiring and boring. Therefore, inspectors do not sense on defect regions.
(5) Inspectors should be inspecting 1.6-2 meters width fabrics at a speed of 20 m/min (D. Brzakovic and N. Vujovic, 1996). It is a hard condition for humans' perceives that reduce the detection rate in inspection systems.
(6) The human based inspection systems could never reach a 100% of detecting rate.
(7) Although Human inspection systems seem less costly, it is limited in finding defects. As a result undetected defects reduce the profit of fabrics.

Because of these vast drawbacks and in order to increase accuracy, attempts are being made to replace manual visual inspection by automated one that employs a camera and imaging routines to insure the best possibility of objective and consistent evaluation for fabric quality.

1.2.3 Automated Fabric Inspection

High cost, low accuracy and very slow performance of human visual inspection has increased interest in automatic inspection systems, so nowadays more researches are working on automatic inspection systems. Automatic inspection systems are designed for increasing the precision, stability and speed with respect to Human Inspection Systems. Beside this, these automatic inspection systems provide high defect detection rates. Moreover, these systems also reduce labour costs, improve product quality and increase manufacturing efficiency (H. Sari-Sarraf and J. S. Goddard, 1999).

The flow chart of an automated inspection system is given in Figure 1.2, generally consists automated inspection systems consist of have four parts: image acquisition, image enhancement (pre-processing), feature extraction and decision making. All the parts in the system need to work in the best way to have effective and efficient inspection software.

1.2.3.1 Image Acquisition

In real-time automated inspection systems CCD (charge-coupled device) cameras, or a CMOS (complementary metal-oxide semiconductor) cameras and a frame grabber used for image acquisition process (M. Mufti,1995), (A. Bodnarova, M. Bennamoun and S. J. Latham, 2000) The cameras are used in two different type; line scan camera or area scan camera. Area scan camera uses a system of area array photo sensors, which can capture images without the aid of a transport encoder. As a result, the image resolutions are not affect from transport speed in both directions. A line scan camera uses linear array photo sensors systems, so linear array photo sensors systems provides a higher resolution and can inspect a larger portion of an inspected product. The disadvantages of these systems are need for a system which usually has to be used to synchronize the camera scan rate with the transport velocity of the product. With a line scan camera, a complete 2D image can be created up from multiple line scans. In real-time automatic inspection systems, resolution is a significant detail for detecting of defects. Image resolution depends on the hardware used and the distance between the camera and the product being inspected. Small image resolution usually leads to a fast inspection but causes to overlook the details and as a result possibility of missing small defects. In contrast, large image resolution leads to detect all the details but decrease the inspection speed.

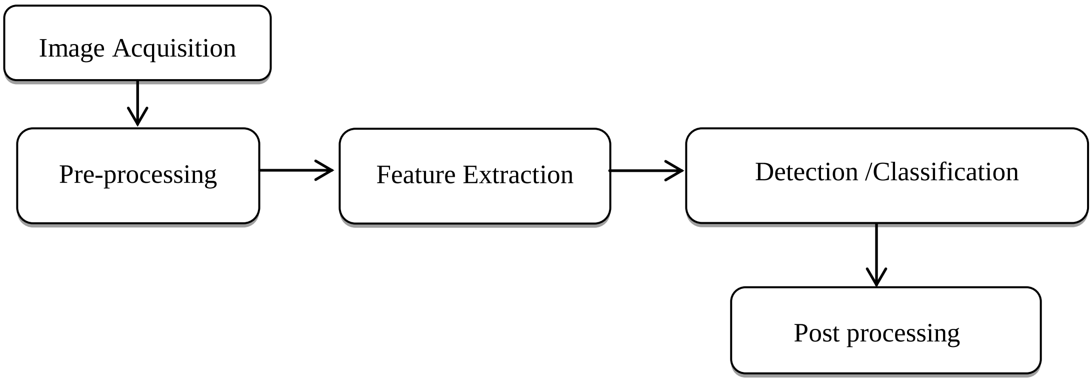


Figure 1.2 Structure of Automated fabric inspection system's flow chart

1.2.3.2 Pre-processing

This part is a pre-processing part which is used to obtain useful information from captured fabric images by feature extraction techniques. Although fabric images are captured in high resolution, the images also include noises and other distortion. Median filtering, histogram equalization, etc. are some applications that use for preclude the adverse effects. Median filtering (S. H. Jeong, H.T. Choi, S. R. Kim, J. Y. Jaung, S. H. Kim, 2001) is used for removing small noises and histogram equalization reduces the effect of unstable illuminations (Y. F. Zhang, R. R. Bresee, 1995). Histogram equalization is so effective. It determines the gray level values, then set new gray-level values of pixels to achieve a more uniform gray-level distribution in an image (R. C. Gonzalez, R. E. Woods., 2002). Histogram equalization can be seen by looking at noticeable changes in contrast. Finally, preprocessed images are isolated from harming affects that making it difficult to perceive the defects. A new modified image is produced for achieving better detection. Beside this, these applications do not change the dimensions and size of the images.

1.2.3.3 Feature Extraction

The aim of feature extraction is to obtain useful information from an image. In the case of fabric defect detection, defected and non-defected texture are characterized and analysed. The relationships or the differentiations define helpful information that is used as features. Features are very importance to most fabric defect detection systems because they possess a close relationship to the detection accuracy of the fabric defect detection method.

In practice, features from textured images are described as feature vectors. For discrimination in fabric images, the feature vectors are realized by measuring those values which are very similar in the fabric defects. The values for defect-free fabrics are measured as well. If better features are obtained, that means better computations and better discrimination shall be done. So the accuracy rate of fabric defect detection is increased. Features are empiricallyverified. In this case, determinations are measured by testing sample by sample, rather than they are compared with some predetermined thresholds. Deviations beyond the predetermined thresholds are counted as defects. Nevertheless, determination of the thresholds is usually subjective, so some errors in defect inspection may still be perceived due to dust particles, and lighting conditions. In other cases, other statistical or soft classification techniques may be used (Y. F. Zhang, R. R. Bresee, 1995)

Consequently, the question to which window size gives optimal discrimination still remains unanswered. As the features extracted for defect detection is crucial, a detailed discussion will be given in chapter 2 where several different feature extraction methods are described.

1.2.3.4 Detection /Classification

This part actually works like the fabric defect detector .In detection and classification section feature vectors are used to determine and classify the patterns to classes. In the detection of fabrics, since there are two classes considered: the normal fabric and the fabric defects. Fabric images will be assigned to only one of these classes. Difficulty of this part is derived from thevariability of the feature values. Therefore, different techniques will be used to determine which type of detectors is more convenient and provides satisfactory results.

1.2.3.5 Post-processing

Fabric defect identification is complete in detecting and classification process, but there are still some samples that are wrongly detected. The faults may lead to give incorrect decisions that cause disposal of more fabric and extra cost may occur on the manufacturing process to reduce the risk, a post-processor is needed after the detection phase. There is no absolute method for post-processing but the common morphological operations of erosion, dilation and opening have been employed as post-processing (Y. F. Zhang, R. R. Bresee, 1995).

1.2.4 Requirements of Automated Inspection Systems

The main disadvantages of existing inspection systems are the high hardware and software development costs, the huge computational efforts are required, and the limited range of the defects to be detected, e.g., defect sizes, defect types, etc. (Kumar A.,2001). So, researches aim to design useful methods or systems by spending minimal costs. The developments in fabric inspection systems' software facilitate to better characterization of defects and patterns. This parameter becomes main requirements of fabric defect detection systems. Also, the other requirements are shown as below (M. Bennamoun, A. Bodnarova, 1998), (T. Li, W. Peter, K.Tim, 1997), (D. Brzakovic and N. Vujovic, 1996):

(1) One of the most important requirements is that the systems should be designed with minimum costs.
(2) Automated inspection systems must provide the needs of the real-time inspection conditions.
(3) The systems must work in different types of fabric patterns.
(4) Performance of Automated inspection systems should not be less than human based inspection systems
(5) Systems should be resisting the bad conditions of textile industry environment both as hardware and software.
(6) The systems should have easy and understandable control mechanism that everyone uses without forcing.

1.2.5 Advantages of Automated Inspection Systems

Automated Inspection Systems are designed for providing the needs of textile industry. In the past 40 years, different techniques of computer vision have been applied to solve automated inspection problems (Nalwa V.S., 1993) and also new or advance systems are developed. The reasons of concentration on automated Inspection systems are shown that the system has more advantages than human based inspection. The advantages are summarized as following (Newman T.S. and Jain A.K. ,1995),(Tolba A.S. and Abu-Rezeq A.N. ,1997, Malamas E.N., Petrakis E.G.M., Zervakis M., Petit L. and Legat J.D., 2003):

(1) The most import advantages is, Automated inspection systems increase the speed and the reliability of inspection.
(2) Fabrics are very sensitive structures. Because of Automated inspection is a non-contact process, it prevents the pattern from disturbances that may occur during contact period.

(3) Automated inspection behaves more stable and involvement is less by the external conditions

(4) High percentages of inspection rates are provided;

1.3 Approaches forAutomated Inspection Systems

The necessary part of inspection software is the fabric defect detection approach, which use feature extraction methods for detecting process. The efficiency of a fabric defect system is highly related with the strength of feature extractor, which is tried to define effective features with strong discriminations between the defect and the non-defected region for fabric defect detection, and use the features in fabric defect classification process.

Fabric patterns have periodic and symmetric structures. The structures break down due to various reasons that called as defects. Also, different types of defects may occur on fabric pattern.In order to overcome all of these problems, patterns must characterize in details. In Automated Inspection Systems feature extraction process obtain the information about defects and non-defected patterns. Feature extraction process is also examine in following four categories:

- Statistical texture analysis approach,
- Texture model-based approach,
- Structural approach,
- Signal processing-based approach.

In the statistical texture analysis approach, gray-level properties are used to characterize the textural property of fabric image or a measure of gray-level dependence, which are called 1st-order statistics and higher order statistics, respectively. The 1st -order statistics, such as mean and standard deviation (B. Smith, 1993), (C. Fernandez, S. Fernandez, P. Campoy, R. Aracil,1994), (S. Ozdemir, A. Baykut, R. Meylani, A. Ercil and A.Ertuzun,1998), rank function (A. Bodnarova, J.

A. Williams, M. Bennamoun and K. K. Kubik,1997), local integration (Y. A. Karayiannis, R. Stojanovic, P. Mitropoulos, C. Koulamas, T. Stouraitis, S. Koubias and G. Papadopoulos,1999), can measure the variance of gray-level intensity among various features between defective areas and background. However, these features weakly measure the spatial texture of gray-level primitives because they are extracted without references to the image context, so if gray-level intensity of defects are not enough different from the pattern, statistical texture analysis approach will show limited performance. The higher order statistics is based on the joint probability distribution of pixel pairs, such as gray-level co-occurrence matrix (YuNan Gong, 1999), (F. S. Cohen, Z. Fan and S. Attali, 1991), gray-level difference method (C. Fernandez, S. Fernandez, P. Campoy, R. Aracil, 1994) and autocorrelation functions. Since higher order statistics carry spatial gray level dependence of the fabric texture, they are able to provide more differentiation of fabric defects than 1^{st} order statistics. However, the disadvantage of this method is that defects size is large enough to enable an effective estimation of the texture property. So this approach is weak in tackling local small defects. Moreover, the computation of higher order statistics is time consuming (A. Bodnarova, J. A. Williams, M. Bennamoun and K. K. Kubik, 1997).

The second category model-based approach, the commonly used techniques is Markov random field Gaussian Markov random field (S. Ozdemir, A. Ercil, 1996). Texture features of a studied texture, and can represent more precisely spatial interrelationships between the grey levels in the texture (Yang 2003). These extracted features are embedded in the parameters of a texture model. The model-based approaches usually identify fabric defects by looking for abnormal model parameters estimated from the inspected fabric texture. Therefore, similar to the approaches based on second order statistics, it is also difficult for the model-based approaches to detect small-sized defects because the approaches usually require a sufficiently large region of the texture to estimate the parameters of the models.

The structural approach use properties of the primitives of the defect-free fabric texture for presence of the defective region, and their related placement rules.

Apparently, the practicability of this approach is to squeeze to those fabrics with regular macro texture.

Unlike the above approaches which discriminates the defects in terms of the visual properties of the fabric texture, the signal processing-based approach extracts features by applying various signal processing techniques on the fabric image. It is expected that the separability between the defect and the non-defect can be enhanced in the processed fabric image. This approach further consists of the following methods:

- Spatial filtering,
- Karhunen-Loeve transform,
- Fourier transform,
- Gabor transform,
- Wavelets transform.

The edges of defects are different from free fabric texture in scale and orientation. Spatial filtering approach aims at enhancing these edge-based differences by designing a set of spatial masks, which enable for easy detection of the defect region. As a disadvantage of this approach, its performance is easily affected by the noise in the fabric image. Karhunen- Loeve transform is able to wrap the energy of the fabric image into a set of uncorrelated coefficients. These coefficients represent optimally the defect-free fabric image, however, not the optimal discrimination between the defect and the non-defect. On the other hand, Fourier transform can be used to capture the periodic structure of the fabric texture, and detect the presence of defects.

Since Fourier based approaches do not have local support in the spatial domain; the features extracted from the Fourier transform are not so effective in detecting small local defects. In fact, fabric defects either appear to be singularities in the homogeneous background, or texture whose primitives are different from the background texture in scale and orientation. Wavelet transform, Gabor transform use localized spatial-frequency analysis at multi-scale and multi-orientation to determine the defects. They are more capable in the discrimination of fabric defects than the other methods that rely on the texture analysis at a single scale (Y. F. Zhang and R. R. Bresee, 1995). Compared to the Gabor transform, the wavelet transform has the advantage of more flexibility in the decomposition of the fabric image (B. Nickolay, K. Schicktanz and H. Schmalfub, 1993). Based on the above discussions, the wavelet transform is viewed as the most appropriate approach to the feature extraction for fabric defect detection.

1.4 Research Objectives

This research aims to design a useful and high detection rate automated visual inspection system software. The use of advanced image processing and signal processing techniques is proposed, including image segmentation and representation, which would effectively detect a variety of defects in textile fabrics. The improvement of this study is to design filters which use Gaussian function called Difference of offset Gaussian (DOOG) and use filters for better extraction of features. Although similar methods have been proposed in the past to detect defects, many problems remain to be solved for practical implementations. Hence, the study described in this thesis involves the following principal objectives:

(1) To design systems that detects more class of defects and also detects the non-defected patterns.
(2) To design effective structure that determines parameters automatically by using type of patterns,
(3) To design a high detection rate system with high detection speed.
(4) To determine the classes of defects that detect from system.

The economic benefit of this research is to reduce the total cost in fabric and garment manufacturing by minimizing rejections due to defects in fabrics, and to enable more effective management of the company's logistics operations. Indeed, the knowledge gained from this project can also be applied to solve similar quality control problems for other industries.

1.5 Outline of This Thesis

Chapter 2.This section is represented a summary of previous works that is designed for Fabric Defect Detection Systems. In terms of the feature extraction method, the existing methods for fabric defect detection are categorized under four headings: methods of using statistical texture features, methods of using textural model-based features, methods of using geometrical features and methods of using signal processing-based features.

Chapter 3: Research is based on detecting defects. This section gives information about defects that how defects can occur and also types of defects are introduced in this chapter.

Chapter 4: This sectionfocuses on the theory of difference of offset Gaussian function technique. Gaussian function and the methods of creating Gaussian function also explained for better understanding the issue of DOOG technique. Parameters and properties of DOOG are introduced respectively. Beside this, Chapter 4 also gives methodology of research. The proposed method is presented in five sections;

- Determination of filter parameters.
- Preliminary stage that image resizing and gray-level conversion are used for preparing the image to processing stage.
- Filter designing.
- Implementations of filter to defected or non-defected fabric images and analyze the features.
- Detecting and classifying defects.

Finally, it will introduce how to design a Matlab Graphical User Interface and how to use the special properties such as graphical icons, visual indicators or special graphical elements.

Chapter 5: This section summarizes and discusses the important findings of defect detection and classification results.

Chapter 6: The thesis is concluded in Chapter 6. Suggestions for future research are also presented.

CHAPTER TWO
REVIEW OF LİTERATURE

This chapter presents the summary of previous techniques on fabric defect detection, additionally compare the good and bad aspects of these techniques .Most of the research have been done for defect detection. Only few researches have been done for classification part. All these fabric defect detection methods are classified into four categories by their feature extraction models (M. Tuceryan and A. K. Jain, 1999), statistical approaches, model-based approaches, geometrical approaches and signal processing-based approaches.

In this part, an automated inspection system structure is also presented. In Section 2.1, 2.2, 2.3 statistical texture features, texture model-based features and geometrical features are summarized. Signal processing-based features are reviewed in section 2.4, which includes approaches using spatial filtering, Karhunen-Loeve transform, Fourier transform, Gabor transform and wavelet transform.

2.1 Methods of Using Statistical Texture Features

Surface of the fabricshavehomogeneousstructure, so non-defect fabric image's gray-level distributions are closely uniform, that's enough to create a statistical texture property from fabric texture. However distributions that are affected by defects generate a difference between statistical texture non-defected and defected texture. The differences give the defects on texture. Statistical texture features which measure the gray-level intensity or the spatial dependence of gray-level intensity are extracted, which are called the first-order statistics or the second-order statistics respectively (M. Tuceryan and A. K. Jain, 1999).

2.1.1 First-Order Statistical Texture Features

The first-order statistics characterize the image texture. For example if mean and standard deviation is taken by using colour or gray level values of texture, a simple statistic features are extracted (R. C. Gonzalez, R. E. Woods,2002).Generally, the standard Deviation has shown better performance than mean method. Because, if a fabric image is exposed by illumination, the difference in the level of local pixels themselves remains almost the same. Using only the mean is hard to discriminate between defect and defect-free regions. But, the standard deviation in a small region reveals a different set of values in different types of regions. Thus, the precision of representing a defected texture is more accurate.

Previous works show that means and standard deviation and Shannon entropy is effective in detecting large areas of defect (M.C. Hu, 2000).Despite of this; the local statistical features are solely good at characterizing those defects whose intensities are sufficiently different from the defect-free regions, e.g. oily stain and holes. This is because the window size affects the extracted information and there is no guarantee of an accurate detection with this method.

Skewness and Kurtosis methods are classified in first-order statistics (K. Y. Song, M. Petrou, J. Kittler, 1992). The skewness is related with symmetry of texture and Kurtosis is related with peakedness of probability data in normal distribution. Skewness and Kurtosis are also extracted in a window and are defined as:

$$\text{Skewness} = \frac{1}{N}\sum\left(\frac{x-\mu}{\sigma}\right)^3 \qquad (2.1)$$

$$\text{Kurtosis} = \frac{1}{N}\sum\left(\frac{x-\mu}{\sigma}\right)^4 - 3 \qquad (2.2)$$

μ denotes the mean, σ denotes the standard deviation, x denotes the gray level intensity of a pixel and N is the total number of pixels in the pattern.

2.1.2 Second-Order Statistical Texture Features

The second-order statistical texture features, which are extracted using gray level co-occurrence matrices (R. M. Haralic, K. Shanmugam and I. Deinstein, 1973), autocorrelation function (R. M. Haralic, 1979), and gray-level difference (R. W. Conners and C. A. Harlow,1980), etc. methods, are classified under second-order statistical texture features, these methods use spatial interrelationships of the gray level intensity in texture. The second-order texture features, co-occurrence matrices-based features have more efficiency to discriminate of texture than other methods (R. M. Haralic, 1979), (P. P. Ohanian and R. C. Dubes, 1992).

Suppose $\{Im(u, v), 0 \leq u \leq (M-1), 0 \leq v \leq (M-1)\}$ denotes an image of size $M \times M$ with G gray-levels, the $G \times G$ gray level co-occurrence matrix C for a displacementvector $\mathbf{d} = (d_x, d_y)$ is defined as follows:

$$C(i,j) = |\{((r, s), (r+d_x, s+d_y)) : Im(r, s) = i, Im(r+d_x, s+d_y) = j\} \qquad (2.3)$$

Where $(r, s) \in M \times M$,

Based on the gray level co-occurrence matrix, R. M. Haralic, K. Shanmugam and I. Deinstein (R. M. Haralic, K. Shanmugam and I. Deinstein, 1973) suggested the extraction of fourteen features for describing different properties of the texture image. Four of them are widely used for texture classification (P. P. Ohanian and R. C. Dubes,1992), which are listed as follows:

- Entropy measures the image complexity.

$$\text{Entropy} = -\sum_i . \sum_j C(i, j) \log C(i, j) \quad (2.4)$$

- Contrast measures the image contrast or the local variations.

$$\text{Contrast} = -\sum_{\text{i}}.\sum_{\text{j}}(\text{i}-\text{j})^2\text{C}(\text{ i},\text{j}) \quad (2.5)$$

- Correlation measures the image spatial dependencies

$$\text{Correlation} = \frac{\sum_{\text{i}}.\sum_{\text{j}}(\text{i}-\mu_u)(\text{j}-\mu_y)\text{C}(\text{ i},\text{j})}{\sigma_u\sigma_v}(2.6)$$

- Energy measures image energy.

$$\text{Energy} = \sum_{\text{i}}.\sum_{\text{j}}\text{C}(\text{ i},\text{j})(2.7)$$

- Dissimilarity checks the image similarity.

$$\text{Dissrimilarity} = \sum_{\text{i}}.\sum_{\text{j}}\text{C}|\text{ i}-\text{j }| \quad (2.8)$$

Correlation, energy, entropy, contrast and dissimilarity are used to extract characteristic features values from fabric defect images and these features are assisted to detect broken warps, broken wefts, holes and oil stains. (C.F. j. Kuo, T.L. Su, 2003). In addition contrast also extract features with using amount of local variation nep, broken end, broken pick and oil stain are detected by using these contrast features (I-Shou Tsai, Chung-Hua Lin, Jeng-Jong Lin,1995).

2.2 Methods of Using Texture Model Features

The aim of this method is to create a much closed texture. In the main title probability density function are used for patterning texture. More specifically, stochastic models generate similar pattern with using gray level interrelationships of texture. The fabric patterns can be modeled by a set of model parameters, all these parameter are used as a feature for texture discrimination.

Most commonly Markov random field (MRF) are used to create a model for the texture images (G. R. Cross and A. K. Jain, 1983), (R. Chellappa and S. Chatterjee, 1985) because MRF algorithms highly describe statistical dependence of the texture image. So MRF has been successfully applied in the field of defect detection for textile fabrics. In MRF, the pixel values are assumed to consist of a noise element plus a value determined in a statistical way by the neighbours of the pixel.

Gaussian Markov random field (GMRF) is a major class of MRF and has been successfully applied in the field of defect detection for textile fabrics. This section will introduce the technique and its applications in defect detection in detail.

Let a point is determined at p=(x,y) coordinates and i_o denotes the intensity of point p that show as $i_o(x,y)$,also $\mathrm{g(x,y) = i_o(x,y) - \mu}$ where $\mathrm{\mu = E\{i_o(x,y)\}}$.The GMRF is expressed by the following difference equation (F.S. Cohen, X. Fan, 1991):

$$\mathrm{g(x,y) = \sum_{z \, \epsilon \, D_p} \beta_{p-z} g(v) + \ e(p)} \quad (2.9)$$

D_p defined as the neighbourhood sets given by:

$$D_p = \left\{ \mathrm{z = (k,l): \left||p - z|\right|^2 \leq \ N_p, z \neq (0,0)} \right\}, \quad (2.10)$$

Maximum Square of the distance is shown N_p. The range of N_p is p to z. n (p) is symbolized the Gaussian noise with zero mean and autocorrelation function given by:

$$\mathrm{E(n(p).\, n(z+p))} = \begin{cases} \sigma^2 \ \text{ if } \ z = (0,0) \\ -\sigma^2 \beta_p - v \ \text{ if } z \epsilon \ Dp \\ 0 \end{cases} \quad (2.11)$$

The GRMF model is parameterized by a parameter set of β_p, r and σ^2 which can be estimated when the model is used to represent a texture image. Therefore, the parameter set can represent features for the discrimination of the image. Fig. 2.1 shows the structure of a GMRF model of the neighbourhood $D_p$with p = 5.

		7	6	7		
	5	4	3	4	5	
7	4	2	1	2	4	7
6	3	1	v	1	3	6
7	4	2	1	2	4	7
	5	4	3	4	5	
		7	6	7		

Figure 2.1The structure of a GMRF model

The model-based approaches are efficient methods that use for fabric image because the MRF-based detection approaches requires less computation and also characterize fabric patterns more firmly in the local texture information. However, in a real application, because of Model based approaches make calculation based on pixel neighbourhood, Model based approaches model are poor in discriminating small local defects, In contrast, the model parameters gives good estimation in large regions.

2.3 Methods of Using Geometrical Features

From a structural view, fabric patterns are combinations of wefts and warps. Wefts and warps are weaved in periodical and symmetrical structure blocks and these blocks create fabric patterns. Geometric approaches use the relationships of the periodic blocks and corresponding placement rule and generate a structural model of fabric pattern (M. Tuceryan and A. K. Jain, 1999). All the distortions, on the symmetrical and periodic structural model, are used as features for defect detection. Defects are easier to find by using these features, so geometric approaches based features are frequently used in defect detection systems. Fabric inspection systems use two geometrical approaches based features for defect detection (D. Chetverikov and A. Hanbury, 2002). Regularity and local orientation (anisotropy), the approaches which use these features is named as "StrucDef". It determines structural defects as regions of abruptly falling regularity. In real application, the approach firstly defines the directional regularity for an angle *i* as:

$$R(i)=[R_{int}(i)R_{pos}(i)]^2 \qquad (2.12)$$

$R_{int}(i)$ represent intensity regularity and $R_{pos}(i)$ represent the position regularity. In order to obtain these two variables, a contrast function F(x) has to be defined, which is calculated from the normalized autocorrelation of the image in the polar representation. The contrast function F(x) is then smoothed by using a filter. The intensity regularity is computed as:

$$F_{int} = 1- \frac{F_{min}}{F_{max}} (2.13)$$

Where F_{min} and F_{max}show the limits of F(*j*), and the following equation, shows how to get position regularity, parameters $x_1 and x_2$ are the positions of the two lowest minima in $F(x)$ ($x_1<x_2$). Sequence of the local maximum values of $R(i)$ are symbolized as $T_l$andobtained from equation (2.12), where l (l =1, ... , l 0) is the index of the maxima sequence, and then is threshold at T_{thr}= 0.15. Two features can be calculated from the sequence threshold: the largest value MR and the mean μR ($0 \leq \mu R \leq MR \leq 1$), which are used to indicate whether a texture is regular or random.

$$R_{pos} = 1 - \left|1 - \frac{2x_1}{x_2}\right| (2.14)$$

Features are containing information about regularity of each sub-window of the studied image, whether windows has low regularity or not. Low regularity represents defected regions and high regularity represents non-defected regions. p_i show feature vector of a sub-window . A central point p_c can be found in the equation:

$$d_{med}(c) < d_{med}(i) \quad \text{for all } i \neq c, \qquad (2.15)$$

Where

$$d_{med}(i) = \text{median} \| p_i - p_j \| \qquad (2.16)$$

r_i is denoted as distance between a point p_i and the centre p_c , which is defined as:

$$r_i = \| p_i - p_j \| \qquad (2.17)$$

Beside this, Chen J. and Jain A.K. (Chen J. and Jain A.K., 1988) designed a different structural approach for detecting defects in textured images. The approach called as skeleton representation that operates on mapping images into special data structure. The approaches use location and length histograms of the skeleton, the statistical measurements for ripple, mean jump and end spell for detect defects.

Geometric approaches are only suitable for detecting fabric defects appearing in a fabric with a regular macro texture. In addition to this disadvantage, such approaches can only detect effectively those defects causing disorders in sufficiently large areas of the texture background. However, geometrical approaches have some problems to characterize a fabric image with a regular micro texture.

2.4 Methods of Using Signal Processing-Based Features

The approaches which discussed above generate features directly from the gray- level values of an image. The features can provide an easy identification with simple and fast ways. However, these approaches may not be very efficient for complex fabric patterns. In this section, the reviews of signal processing methods are revised. These methods include some filtering or transform operations for extracting features for the discrimination of fabric defects.

2.4.1 Spatial Filtering Approach

This method characterizes the patterns by using the structural extensions. The obtained features change according to characteristics of the used filters. In contrast to previously surveyed methods, the advantage of this method is to provide efficient features in micro weaved fabrics. Fabric patterns are characterized in terms of edge responses by using various types of spatial filters (T. Randen, 1997). Defected regions lead to changes on the non-defected fabric pattern. Various types of spatial filters use these differences and generate dissimilar edge responses that allow differences between defects and non-defect fabric regions. In addition, defect responses to edge of defected regions provide features about defected region coordinates, which is the advantage of their method, so redeem to design an alternative process to determine the defect region coordinates. The block diagram of Spatial filtering approach used fabric defect detection is shown in figure 2.2.

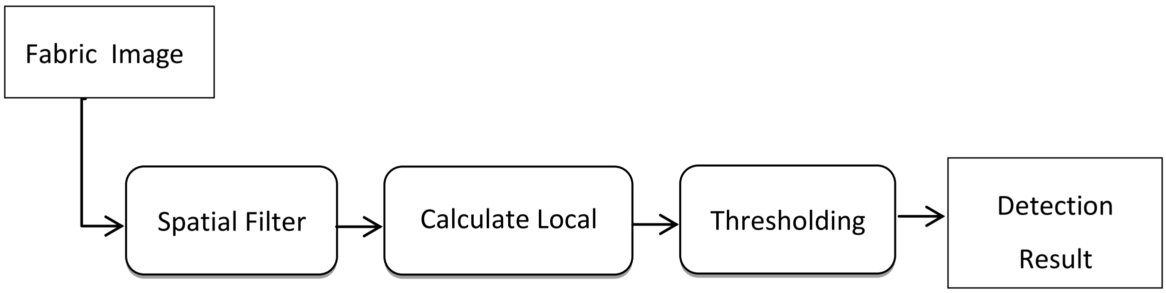


Figure 2.2Spatial filtering approach to fabric defect detection

Spatial filtering masks are ordinarily applied to fabric images by using convolution. After convolution process, some energy responses are occurred due to the layout and the differences in the pattern. Local energy features may also include noises, so thresholding is used to eliminate the lower energy responses for obtaining the exact defect region. Some advanced spatial filtering approaches include several processes for better defect region segmentation.

If we look at previous studies using this method, S. Ozdemir, A. Baykut, R. Meylani, A. Ercil and A.Ertuzun attempted to detect defects regions by using a two-dimensional adaptive lattice filters (S. Ozdemir, A. Baykut, R. Meylani, A. Ercil and A.Ertuzun,1998). After the filtering process, defect features consist by using incalculable energy responses that include only defect regions' energies. This method was improved by (D. Chetverikov, 1988). An edge detector is inserted after filtering process and is used for increasing the defect regions border energies, and then thresholding gives exact information about defect region. However, it was found that the shape and size of the detector window should be similar to that of the defect, which means this approach has limited flexibility in defect detection. Neubauer (C. Neubauer, 1992) design linear filters for detecting defect regions. In contrast to other methods, histogram of filtering process output creates the features. The test results showed detection accuracy as 98.3% and 90.6%, respectively. F. Ade, N. Lins and M. Unser use Karhunen-Loeve, Hadamard, sine and cosine and Law's filter masks in fabric defect detection (F. Ade, N. Lins and M. Unser, 1984). It was found that Karhunen-Loeve transform is the best and Law's masks obtained similar performance with the orthogonal transform. Fazekas et al. first adopted special illumination arrangement to enhance the visual effect of the defects pilling or wrinkle (Z. Fazekas, J. Komuves, I. Renyi and L. Surjan, 1999). Then a grayscale morphological filtering was performed on each image for the enhancement of defects. Dewaele et al. designed a set of filters for the detection of texture defects. The shapes of the filters were determined based on the estimation of the texture period, while the filter coefficients were determined by Eigen filter extraction. It is noted that their method is independent of the resolution of fabric image (P. Dewaele, P. Van Gool and A. Oosterlinck, 1988).

The spatial filtering approach has been widely used for fabric defect detection. However, the designed filter(s) are only efficient for a limited number of defect classes, due to the different spatial-frequency characteristics of various classes of fabric defects. Moreover, the spatial filtering approach is sensitive to the noise in the fabric image.

2.4.2 Karhunen-Loeve Transform Approach

Karhunen-Loeve transform uses some constants to classify the energy values which are obtained from original image. Features occur by using these classified energies. Karhunen-Loeve Transform Approachanalyse these classes because defects' energies and non-defected fabric patterns' energies are located in different classes. This method is also known by different name that is eigenvector transforms. If transforms are examined theoretically (R. Gonzalez and R. Woods, 1992), (M. Unser and M. Eden, 1989). Gray-level intensities of pixels in an image are represented by x, μ denotes the mean vector:

$$\mu = E\{x\} \tag{2.18}$$

Covariance matrix is denoted as C and calculated as following:

$$C = E\,\{(x - \mu)(x - \mu)^T\} \tag{2.19}$$

Then the eigenvectors $\mathbf{e}_i$and eigenvalues $\beta_i$of the covariance matrix **C** are calculated which satisfy,

$$C\mathbf{e}_i = \beta_i \mathbf{e}_i, \text{ for } 1 \le i \le d \tag{2.20}$$

The Karhunen-Loeve of the vector ***x*** is defined with eigenvectors as follows

$$\mathbf{v} = [\mathbf{e}_1, \mathbf{e}_2, \ldots, \mathbf{e}_l]^T.x \tag{2.21}$$

Ozdemir et al. tried to detect the defects on fabric pattern by using K-L transform (S. Ozdemir, A. Ercil,1996). Eigenvectors designate as transform coefficients.

Studied images are processed into pieces. Sum of the largest three eigenvalues are used for identifying the pieces of images. Fabric patterns vector features has normal levels but defects region pieces has anomalous levels that a differentiation to detecting the defects. In addition, new K-L transforms used detection process is design by Mamic and Bennamoun (G. Mamic and M. Bennamoun, 2000). This method use also Neyman-Pearson detector with eigenvalues for detecting the defects.

Some disadvantages of this method are reducing the number of studies in textile industry. K–L transform approach based on optimality property of the fabric texture, if there is not an optimal difference between defect and non-defect pattern. This approach faces major challenges.

2.4.3 Fourier Transform Approach

Fourier transform translate the calculations between time domain and frequency domain knowledge, as well asit is a very useful method for analysing periodic signals due to the algorithmic structure of the Fourier transform. Domain and Fourier transform is a very suitable technique for analysing periodic signals because of certain desirable properties, including noise immunity and translation invariance (A. Boggess, F. J. Narcowich, 2001). Fourier transform is a well-known technique that relates the frequency and time. It characterized the objects as complex valued functions in two dimensional structures, and all of these processes are performed in frequency domain. In parallel, a magnitude spectrum is formed, magnitude spectrum contains information about the Periodicity and directionality of the pattern, also periodical and directional disturbance can change the peaks in spectrum. These differences lead to identify the deformity on signal or patterns (C.H. Chan, G.K.H. Pang, 2000). Periodic structure of fabrics makes Fourier transform suitable for use during the detection process. Fourier transform will also have a regular, crystalline structure of isolated peaks (Lois M. Hoffer, Franco Francini, Bruno Tiribilli, Giuseppe Longobardi, 1996). A defect on the fabric has expanded over a region in the magnitude spectrum. In the same way, sizes, shapes and spread of defects change the peaks of magnitude spectrum to higher or lower frequencies values. Therefore, the spectrum gives ideas about the regularity of fabric patterns and the features that assist to define defects (C.H. Chan, 2001).

Let M and N be the length and width of an image, F (fx, fy) be the Fourier transform of f(x,y) with $f_x$and $f_y$as the spatial frequencies. The general equation of a two-dimensional Fourier transform is defined as

$$F(m,n) = \frac{1}{N^2}\sum_{x=1}^{N-1}.\sum_{y=1}^{N-1} I(x,y).\,e^{-\frac{j2\pi(xm+yn)}{N}} \quad (2.22)$$

Since F(f_x , f $_y$) is a complex function, it can be decomposed into a real part Fr (f_x , f_y) and an imaginary part Fim (f_x , f $_y$). The magnitude spectrum M(f_x , f $_y$), phase spectrum ø(f_x , f $_y$) and power spectrum P(f_x , f $_y$) are then obtained by

$$M(f_x, f_y) = |F(f_x,f_y)| = \sqrt{F_r{}^2(f_x,f_y) + F_{im}{}^2(f_x,f_y)} \quad (2.23)$$

$$\varnothing(f_x, f_y) = \tan^{-1}\frac{F_{im}(f_x,f_y)}{F_r(f_x,f_y)} \quad (2.24)$$

$$P(f_x, f_y) = F_r{}^2(f_x,f_y) + F_{im}{}^2(f_x,f_y) \quad (2.25)$$

In study (I-Shou Tsai, Ming-Chuan Hu, 1996), a fabric defect detection system is designed by using Fourier transform. Fourier power spectrum of a fabric pattern created as a feature for detecting process. Warp and weft densities determine the variables of power spectrum. The features can convey to artificial neural network process which can identify the defects. This research can determine only missing end, a missing pick, a broken fabric and an oily fabric defects.

Since a fabric is similar to a 2D grid, the corresponding optical Fourier transform may appear stationary when the fabric is moving evenly. A research used this characteristic to design a defect detection scheme (Hoffer L.M., Francini F., Tiribilli

B. and Longobardi G., 1996). The scheme can detect potential defects with a back propagation network, in which a small subset of pixels from an acquired image is used as the input. Another survey conducted by Campbell J.G., Fraley C., Murtagh F. and Raftery A.E. (Campbell J.G., Fraley C., Murtagh F. and Raftery A.E., 1997) that use Fourier transform and morphological conjunction, Hough transform and model-based clustering techniques to create features for defining the defects on fabric pattern.

In 2000, Fourier transform based Fabric defect detection system is designed (C. H. Chan and G. Pang, 2000). The properties of detection process convert the outputs of Fourier transform to two central spatial frequency spectrums. The information that is obtained from these spectrums can assist to determine different types of fabric defects.

Tsai and Hsieh‘s research use Fourier and Hough transform to detect the defects on textile fabrics (Tsai D.M. and Hsieh C.Y., 1999). In detecting process, transforms are separately applied to the fabric pattern. Fourier transform is used for characterized the pattern and Inverse Fourier transform is used to transform information from frequency domain to time domain, as well as Hough transform is used for deleting the line patterns in the image. The features that are obtained from transform are combined on grid. Also, system determine thresholding levels for recognize the defects.

Fabric patterns are symmetric or periodic structures. So, Fourier transform generally efficiently work in Fabric defect detection systems. However, obtained features include raw information. They haven’t got mean before extra processing, so Fourier transform based system must contain a neural network process to get meaningful features. Also, large defect regions and some small defects make limp for Fourier transform based systems. Large defect regions disrupt the periodicity of pattern which is badly affect in determination of complex valued functions and small defects are hard to detect by Fourier transform.

2.4.4 Gabor Transform Approach

J. G. Daugman can recognize the simple cells in the visual cortex and modelled cells by using Gabor functions. Frequency and orientation representations of Gabor filters provide a convenience to analyse the textural patterns. In the time domain, a 2D Gabor filter is a Gaussian kernel function modulated by a sinusoidal plane wave. Gabor filters which are used in applications look in very complex structure, but they are deriving by the dilation and orientation of main wave.

Impulse response of Gabor filter is determined as multiplication of harmonic and Gaussian functions. Because of multiplication property of Convolution theorem. Impulse response of Gabor filter is obtained after the convolution of harmonic and Gaussian functions that are represented in frequency domain. Filters becomes in a complex structure which consist of real and imaginary parts. The Gabor filter algorithm is shown in following equation:

Complex;

$$g(x, y; \lambda, \theta, \psi, \sigma, \gamma) = exp\left(-\frac{x'^2+\gamma^2 y'^2}{2\sigma^2}\right) exp\left(i\left(2\pi\frac{x'}{\lambda}+\ \psi\right)\right) \quad (2.26)$$

Real;

$$g(x, y; \lambda, \theta, \psi, \sigma, \gamma) = exp\left(-\frac{x'^2+\gamma^2 y'^2}{2\sigma^2}\right) cos\left(2\pi\frac{x'}{\lambda}+\ \psi\right) \quad (2.27)$$

Imaginary

$$g(x, y; \lambda, \theta, \psi, \sigma, \gamma) = exp\left(-\frac{x'^2+\gamma^2 y'^2}{2\sigma^2}\right) sin\left(2\pi\frac{x'}{\lambda}+\ \psi\right) \quad (2.28)$$

Where

$$x' = x\cos\theta + y\sin\theta \quad (2.29)$$

And

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

In this equation, λ denotes the wavelength of the sinusoidal factor, θ show the orientation of the normal to the parallel stripes of a Gabor function, ψ define the phase offset, σ is the sigma of the Gaussian envelope and γ specifies the ellipticity of the support of the Gabor function. This filter often results in characteristically striped response. Filter selection is based on the frequency and orientation properties of a Gabor filter which are explicitly expressed in its frequency domain representation. The Fourier transform of $g(x, y)$ is expressed as

$$\mathrm{H(m,n)} = 2\pi\sigma_x\sigma_y\{e^{-\frac{1}{2}\left(\frac{(m-m_0)^2}{\sigma_m^2}+\frac{n^2}{\sigma_n^2}\right)} + e^{-\frac{1}{2}\left(\frac{(m+m_0)^2}{\sigma_m^2}+\frac{n^2}{\sigma_n^2}\right)}\} \qquad (2.30)$$

Where $\sigma_m = 1/\ 2\pi\sigma_x$ and $\sigma_n = 1/\ 2\pi\sigma_y$. The selection of Gabor filters for texture analysis is based on the centre frequencies and the orientation (A.K. Jain and F. Farrokhnia, 1991) (T. Randen and J.H. Husoy, 1994). Centre frequency can obtained as values :$\frac{1}{\sqrt{2}}$, $2\sqrt{2}$,$4\sqrt{2}$, … , $\frac{Nc\sqrt{2}}{4}$ and the filter rotations degrees are 0°, 45°, 90°, 135°. The orientations degrees guarantee that places which high frequency filter passes are mirrored on image array.

In textile industry, Gabor filters designed as multi-stage structure to get better detection that is shown in figure 2.3. Different Gabor filters are represented in several orientations values.

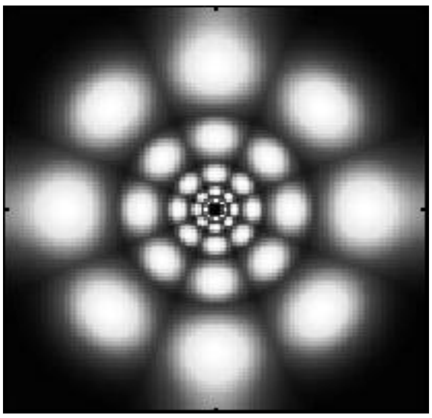


Figure 2.3The defect detection approach using Gabor filters (A. Kumar and G. Pang, 2000).

A number of researchers applied the Gabor filtering method in fabric defect detection systems. Gabor filters are applied to fabric patterns, in multichannel Gabor filter bank (T. Randen and J.H. Husoy, 1994). Parameter that determine the variables for characterizing the textures, are less than enough. Therefore, the methods identify only the few types of defects. Gong et al. proposed an algorithm by using Gabor filter (YuNan Gong, 1999). Gong's research is used in two different ways. First approach is increase to the response which is the difference between defect and non-defected fabric region and the second approach is based on the direct recognition of fabric defects.

In (J. Escofet, R. Navarro, and M. S. Millan, 1998)research, variable frequency and orientation values based pyramidal structure is designed to determine the parameter of Gabor Filters. At the research of Kumar and Pang, Multichannel Gabor algorithms adapt the responses with use Bernoulli's rule for detecting the defects on texture patterns (A. Kumar and G. Pang, 2000).

In research (Beirao C. and Figueiredo M., 1994), two different Gabor filter is used for Fabric defect detection systems. One is multi-channel and other filter is complex-valued Gabor filter. After filtering process, a global Gaussian model, a nearest neighbour method and a local Gaussian model are applied the filter output to extract more precisely defect region detection.

Gabor filter is a popular a method which is also used in Fabric defect detection systems. Large sets of Gabor filter gives advantages to characterize all differentiation in different directions. However, it cause to make hard computations and too much features will lead to information pollution. Therefore, more efforts are needed to study the methods of designing Gabor filters for detecting fabric defects

2.4.5 Wavelet Transform Approach

Wavelet transform is a method that can characterize and extract features both in spatial and frequency domain. An important property of wavelet transform is, an hierarchical framework is generated for analysing the multi-scale and multi-orientation properties of the image (S. Mallat, 1989). In pattern recognition, multi-scale algorithms are analysed patterns until even the thinnest details, and then characterize the features (S. Mallat, 1996). Multi-scales algorithms obtain strong features by separating the image parts in single scale data. These properties of wavelet transform increase the use of wavelet transform in pattern recognition. Patterns have different structures that cause to have different scales and orientations. Wavelet transform examine and analyse these properties to characterize the textures. Wavelet transform is effectively used on pattern recognition and they are also used in Fabric defect detection systems (H. Sari-Sarraf and J. S. Goddard, 1999), (S. Kim, M. H. Lee and K. B. Woo, 1999). Fabric defects are textural distortions which disrupt the symmetry and regularity of fabric pattern. So, texture's scales and orientations can locally change depend on the location of defect regions. The differences lead to build features to detect the fabric defects.

In wavelet transform process, signal decomposes with calculating the internal inputs in the type of $\{\psi_{s,t}(x)\}$

$$Wf(s,t) = < f, \psi s, t > = \int_{-\infty}^{+\infty} f(x)\psi^{*}_{s,t}(x)dx \quad (2.31)$$

$*$ is a symbol of the complex conjugate. *s,t are* $\in$R, $s \neq 0$. $\{\psi_{s,t}(x)\}$ functions are calculate by scaling and translating a function $\psi(x) \in L^2(R)$,$L^2(R)$ shows the vector space of measurable, square-integrable one dimensional functions:

$$\{\psi_{s,t}(x)\} = \frac{1}{\sqrt{s}}\psi\left(\frac{x-t}{s}\right) \quad (2.32)$$

The *wavelet* function $\psi(x)$ should satisfy the following acceptability condition (S. Mallat, 1999):

$$C_{\psi} = \int_{-\infty}^{+\infty} \frac{|\psi^{\wedge}(w)|^2}{|w|} dw < \infty \qquad (2.33)$$

$\psi^{\wedge}(w)$ is a variable that shows Fourier transform of wavelet transform. The acceptability condition pin down the wavelet transforms to get zero average

$$\int_{-\infty}^{+\infty} \psi(x) dx = 0 \qquad (2.34)$$

This property of wavelet transforms cause to decompositions at high frequencies in its Fourier transform. The wavelet transform is an efficient method that obtains features both in time and frequency domains. $\{\psi_{s,t}\ (x)\}$ functions are also found in both domains. Especially sharper time is found at higher frequencies, so basis functions generates efficient features about the texture (I. Daubechies, 1992).

In Fabric defect detection system, the wavelet transform is applied to fabric image by convolving an image with a set of dilated wavelets with spatial orientation selectivity. The decomposition of the image by using the wavelet transform yields multi-resolution and multi-orientation representationsof the image (S. Mallat, 1999), which is appropriate for interpreting the image information.

Most commonly used method that enhance the detection process, is wavelet transforms. Sari-Sarraf and Goddard (1999) designed a fabric detection system built by using multi-scales wavelet representations (MSWAR). Daubechies D2 low-pass and high-pass filters used for facilitate application of transforms(S. Mallat, 1999), Multi-scales wavelet representations (MSWAR) system use shift invariance properties and also get full resolution fabric images that is important for analysing fabric images clearly. In pre-process, images are analysed with wavelet transform, after that non defected fabric patterns' energies are reduced and defects' energies are raised. In detecting process, features can obtained after analysing these differentiation and features are characterized global homogeneity of the images. Disrupting the global homogeneity show the defected regions coordinates. Last part of detection process is using thresolding to eliminate the faulty features and detect the exact place of defects.

Another research based on Mexican hat wavelet filter is designed by Kim et al. (S. Kim, M. H. Lee and K. B. Woo, 1999). Research is to analyse the fabric patterns in vertical and horizontal directions and features are stored in one dimensional data store. Finally, optimal scales are used for reducing the noise effect. Kim et al. also similar performed studies on adaptive wavelet based approach to extract texture features for developing defect detection process in 2005. Lambert and Bock preclude the subsample of wavelet transform for the sake of a shift invariant representation and full resolution decomposition (G. Lambert and F.Bock, 1997). Tsai and Hsiao studied on a new research to develop fabric defect detection (D. M. Tsai and B. Hsiao, 2001). Tsai and Hsiao used wavelet reconstruction to create a reference defect pattern, and then subtract the reference pattern from original fabric pattern, so the defects energies are sharped which gives a clue about defects.

Different feature extraction methods also used with wavelet transform for reinforcing the detection and classification process. In Ref. (Y. A. Karayiannis, R. Stojanovic, P. Mitropoulos, C. Koulamas, T. Stouraitis, S. Koubias and G. Papadopoulos, 1999), Karayiannis et al. extracted Gray LevelDifference Method-based features from sub-bands of the wavelet transform for fabricdefect classification. Amet, Ertuzun and Ercil use Markov random field and co-occurrence approaches to obtain more efficient features from the output of wavelet transform (A.L. Amet, A.Ertuzun, A.Ercil, 2000).As a result of the tests, it shows the feature extraction used wavelet transform are better than simple wavelet transform.

In this section wavelet transform based fabric defect detection systems examined. The wavelet transform analyse the fabric pattern better than other methods, so this approach is less affected from noise, irregular lighting. Also the formed reference patterns are directly extracted from original image that increase the efficiency of obtained features.

2.5 Summary

In this section, available methods were reviewed and also their advantages or weak properties were analysed. All the methods are used to obtain features for better fabric defect detection system. Statistical approaches are examined in two methods. One is first-order statistical texture and other method is Second-order statistical texture. First-order statistical texture has more simple structure, so the method generates the features faster than other methods. But, the method work properly if there is enough difference between defects and non-defected background’s gray levels. So, it is limited efficiency in Fabric defect detection systems. Second-order statistical texture methods characterize the pattern by using pixel gray-level relation between its adjacent pixels. As a result of this, these methods take longer time to make processing. However, method achieves detecting process if the defect regions must have enough contrast difference than background. Textural model features work in same logic like second-order statistical texture. Textural model features obtain the features by using the gray-level relations of fabric textures’ pixels. So, it has problems to identify small defect that does not enough change to be recognized. Furthermore, signal processing-based approaches are reviewed in this chapter. Spatial filtering approaches are efficient feature extractor. If exhaustive filters are used, several classes of fabric defects can recognize. But, the disadvantage of this method is its sensitivity to the noise in the fabric image. Karhunen-Loeve transform approaches obtain features by using optimal representations. However, researches did not give the expected results in small defect detection. Fourier transform approaches generate the features in frequency domain. Although method is widely used in fabric defect detection systems, it does not detect the defects that has small region. Gabor transform approaches analyse the fabric patterns better than others, because it use multi-scale and multi-orientation property to design filters. So, filters act as a multiple filters that obtain more features about defects. But, the multiple structure cause to increasing in the number of computations and the size of data store. Wavelet transform approaches has the same processing principles like Gabor transform approaches. Wavelet transform approaches only has an advantage that is, more interfering structure.

Finally, the best discussed approach is signal processing-based approaches. Methods of processing-based approaches have some weak or usefulness parts. Our research technique is classified in spatial filter methods which contain two advanced filter that called Difference of Offset Gaussian Filters. All the weak or usefulness parts of other methods can notice during the designing of filters and more comprehensive filter can designed which will be examine in the next chapters.

CHAPTER THREE
FABRIC DEFECTS

Textile industry is an emerging sector.Growth and development of the sector naturally bring to increase the spending money. However, textile industry encountered with a number of problems like every sector. They cause some precaution to reduce the impact of losses that are financial losses,customer dissatisfaction, time wasting, need for more resources, etc. Fabric Defects is one of the biggest challenges facing the Textile industry. Manufacturers took various methods to avoid the effects of fabric defects. For example, observation workbench, much more inspectors, slowest manufacturing process, etc.,but they still are not enough also slowdown in manufacturing, the cost of an observation workbench and increase in the number of salaries which are paid to inspectors generate new financial problems. Even the solutions are so troublesome. Automated Fabric Defect detection systems have started to develop with evolving technologies and began to replace with Human based inspection systems. In order to develop better Automated Fabric Defect detection systems, fabric defects must be known and described better.

This chapter is a review of fabric defects. Firstly, definition of fabrics is explained. Fabrics consist of yarns and fibres create yarns. With technologic developments in textile, different types of fabrics can be weaved as woven fabrics. Fabrics’ structures can occur as a product of symmetric and periodic knitting of yarns. In general the yarns are classified in two classes that are perpendicular to each other which are named as Warp and Weft yarns. Warp yarns proceed in line with longitudinal direction of fabrics and Weft yarns proceed in line with sidelong direction of fabrics. Woven fabrics are most commonly produced in industrial fabrics. Therefore, such fabrics are used in this research. Next section gives description of fabric defects and sources of defects and in section 3.2, types of fabric defects and their reasons can examine.

3.1 Definition and Sources

Fabric defects are defined as distortions which occur on fabric pattern. Distortions cause to changing in Warp and Weft yarns, density of yarns or in spaces between Warp and Weft yarns. The automated fabric defect detection systems detect the extraordinary changings and decide the asset of defects and their places. Fabric manufacturing occurs in many stages, which start from manufacturing of yarns. In yarns manufacturing, fibres are processing for composing yarns. However, natural structure of the fibres or spinning operations may cause thinning, thickening, rupturing on fibres, these structural changes cause defects on fabric patterns. After yarn manufacturing, weaving process composing fabrics with using yarns. The yarns are weaving by using looms. Unfortunately, sharpness parts of looms, abnormal motions of machines' reeds are also determine as defect reasons. All the defects that occur during these processes are named woven fabric defects.

3.2 Types and Reasons

Fabrics are produced after passing many processing. Different machines and techniques are used during processing stages. So, fabrics are exposed to forces and stresses which cause defects. According to their forms and directions, defects take different names. The following descriptions summarize the most common fabric defects, and their reasons (HiteshChoudhary, 2005), (Aasim Ahmed, 2000) and table 3.1 shows the appearance of fabric defects with their types (A. S. Malek, 2012).

3.2.1 Floats

Extensions of a part of threats or ends or picks are woven as stuck. It is caused by interposition of warp and weft yarns that create irregulars shapes in a certain area on fabric's patterns.

3.2.2 Weft Curling

Weft and warp threads can twist during weaving process for forming the fabric pattern.More twisted parts of the weft threads named as weft curling defects. It is caused by applying much twisting or less twisting on weft threads.

3.2.3 Slubs

Regional defects that are bringdeterioration on structural symmetry between yarns. It is caused by an extra piece of yarn that is woven into fabric. These defects are composed due to the structural disorders of fibres.

3.2.4 Holes

This is self-explanatory. Faults on weaving machines cause these defects.

3.2.5 Oil Stains

Oil smeared regions can defined on the fabric patterns. It is caused by much lubrication of machines or externally taints the oil on fabrics.

3.2.6 Stitching

Fabric regions that are not weave as a desired forms or disorder of fabric. It is caused by a result of any unwanted movements of weaving machines such as: shedding, picking, etc.

3.2.7 Knots

Knots regions are connecting togetherends of the yarns. The regions are shown as fluffy parts. The reason of these defects is, the broken or finished yarns are floated for maintaining the continuity of weaving process.

3.2.8Irregular Pick Density

It is a mechanical defect described as a jammed or opened areaformed in the fabric due touneven pick density and caused by anirregular beating up.

3.2.9 Snag

Yarns pulled outward from its normal pattern represent the snag type fault. Defects can occur with sharp objects rubbing the fabric pattern.

3.2.10 Tear

Tear defects has similar structures with hole defects. But tears have irregular shapes. Cloth rolls can be torn with sharp edges or rigid object that use in manufacturing processes or damaged gears on machines.

3.2.11 Gouts

A foreign piece of yarns weave as original yarns that cause to a different appearance on fabric surface. These defects have same directions with weft and warp. Pollution in the production area and foreign particles which mix in structure of yarns are the main reasons of these defects.

3.2.12 Snarls

Weft and warp threads can twist for creating fabric patterns. These defects are shown as twisted distortions on patterns. It is caused by friction force that is increased due to high twisting rates of looms.

3.2.13 Miss-end

The absences of threads occur in warp direction. Defects can be in short or long distance. Wrong wrap weaving time in manufacturing processing can miss the weave the warp threads, so these defects can occur.

3.2.14 Stripes

One or more different defects can occur in a zone at the same direction. It is caused by scrape or friction between threads and machines' combs or improper reeding.

3.2.15 Tight/Slack Warp Thread

A yarn or parts of yarn are tighter or slacker than the others in warp direction. Mistaken tensions are the main reason of Tight/Slack warp thread defects.

3.2.16 Double Ends

Two ends yarns are abreast weaved without weft yarns between them. It is caused by fault in warp weaving. Weaving machine skip to weaving the weft direction threats, so two or more ends yarns becomes side by side.

3.2.17 Smash

Many warp threads break down the pattern. It is caused by a wrong timing of shedding, soft picking, insufficient checking of shuttle in the boxes, severe slough off, and damaged or broken picking accessories.

3.2.18. Open Reed

A warp way crack is caused by a damaged or defective reed.Defective or damaged reed is reason for these defects.

3.2.19 Miss-pick

The absences of threads occur in weft direction. Defects can be in short or long distance. Wrong weft weaving time in manufacturing processes can miss the weave the weft threads, so these defects can occur.

3.2.20 Double Picks

Two picks yarns are abreast weaved without warp yarns between them. It is caused by fault in weft weaving. Weaving machine skip to weaving the warp direction threats, so two or more picks yarns becomes side by side.

3.2.21 Coarse-pick

A weft thread or pieces of weft thread which are coarser than the otherpieces/threads. The presence of a weft thread causes this defect that has different count than the other weft threads.

3.2.22 Tight/Slack Weft Thread

A yarn or parts of yarn are tighter or slacker than the others in weft direction. Mistaken tensions are the main reason of Tight/Slack weft thread defects.

Because of the wide variety of defects as mentioned previously, it is too difficult to training withall defect types, so it is useful to study with the most confronted fabric defects.Hole, oil stain, float, coarse-end, coarse-pick, double-end, double-pick, irregular weft density, miss-end, and miss-pick defect images are used to check the success of system. However defects have some variable conditions that complicate to detection process. Firstly, there are large numbers of defects types, also the structures of defects that are change in size, direction which complicate the detection of defects. In the same time, the defects are randomly distributed on fabric images,so the defects exist in the top, bottom, right or left side of the image.

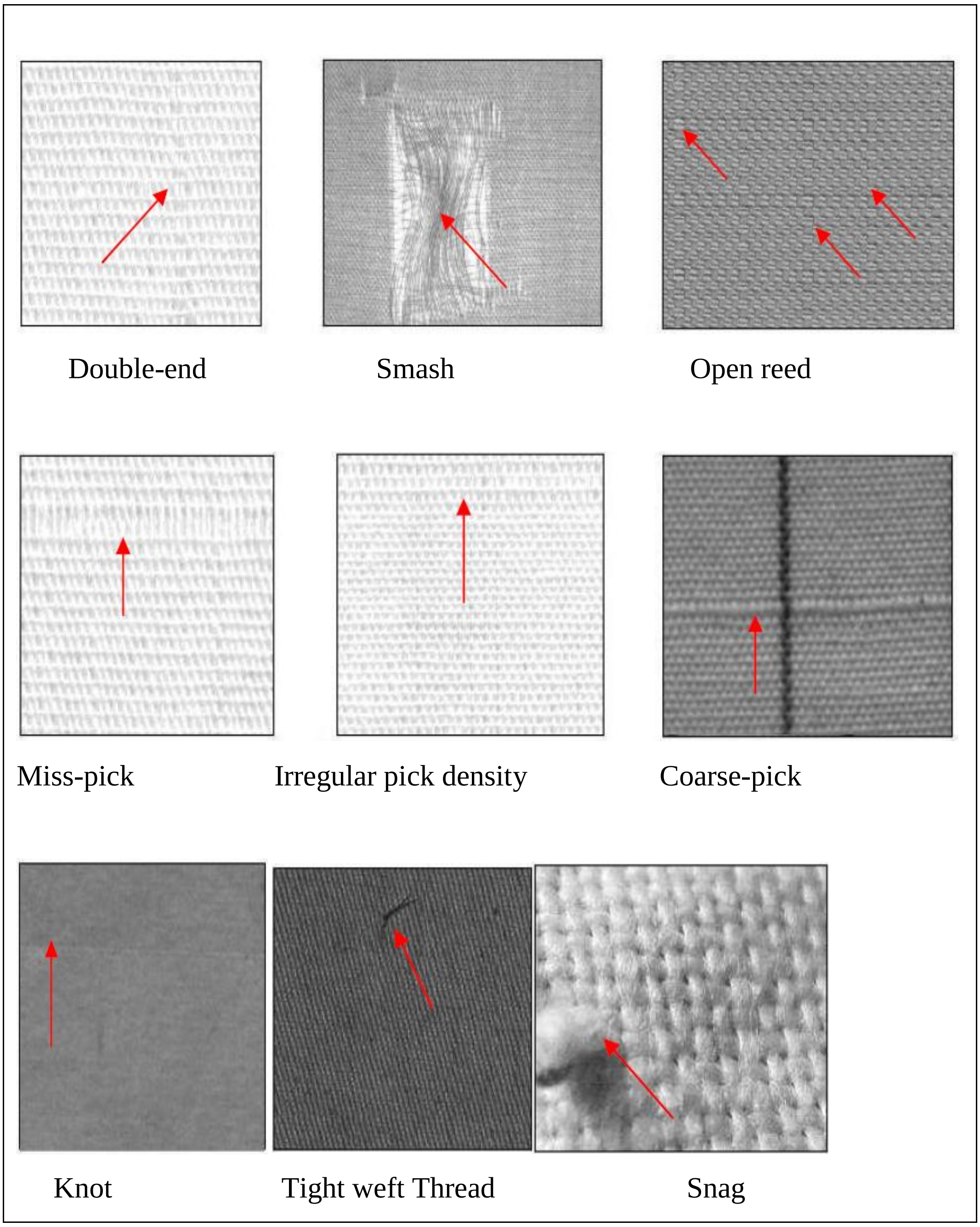


Figure 3.1 Some type of fabric defect

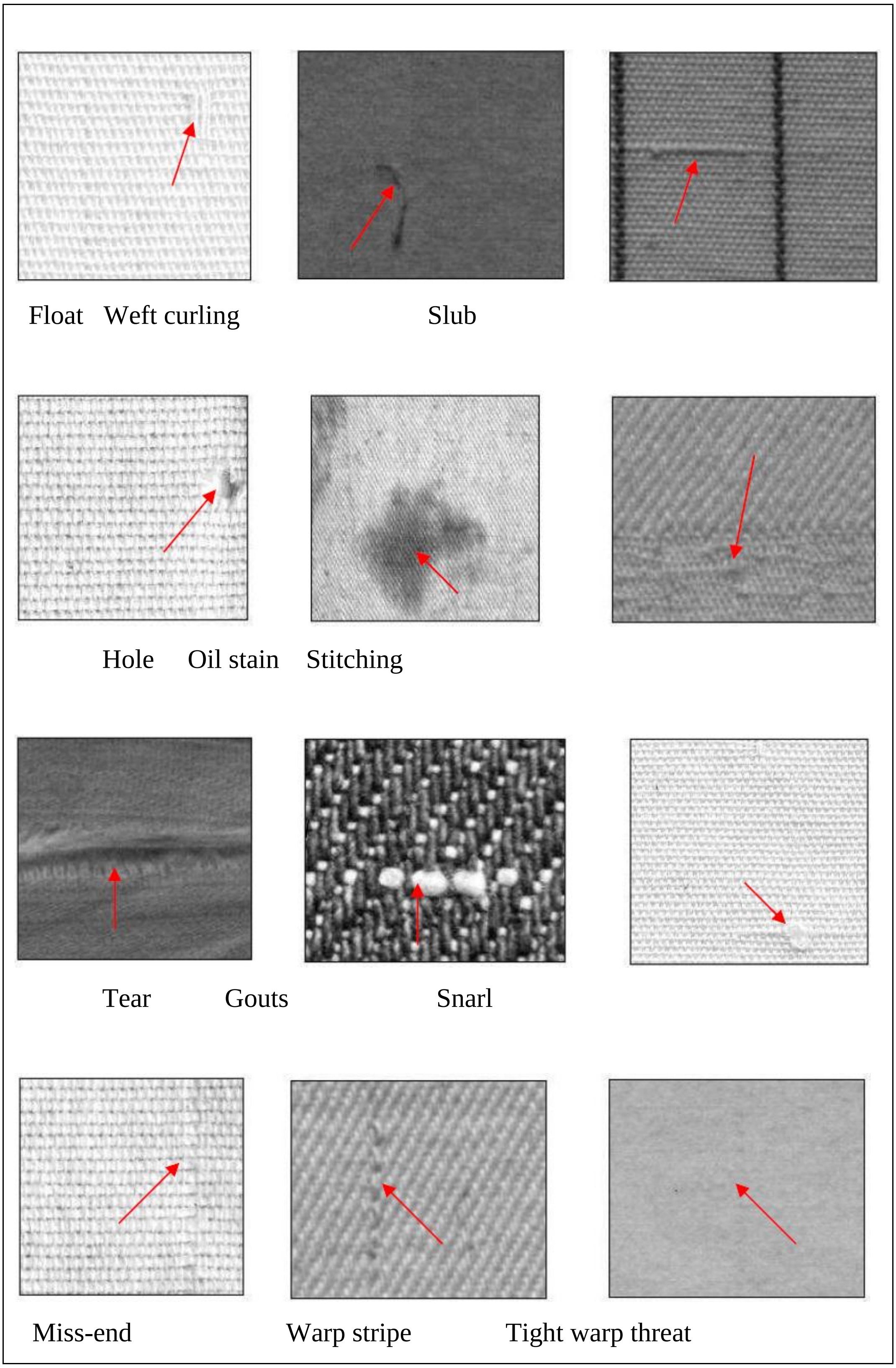


Figure 3.2 Some type of fabric defect.

CHAPTER FOUR

DIFFERENCE OF OFFSET GAUSSIAN FILTER BASED FDDS AND ITS APPLICATION

4. 1 Introduction

Many techniqueshave been designed to improve Fabric Defect Detection Systems so far. Therefore, the aim of this research is to develop a more efficient technique forFDDS. Method of this research is based on Gaussian functions which are called as Difference of offset Gaussian Filters. This section is a review about theory of DOOG filter and their properties. Research’s method classified in signal processed based approaches and in spatial filtering methods as a sub-class. DOOG filters are Gaussian based edge detection technique. Edgesare defined as sharpness changes in intensity of gray-level images (Wei-Ying Ma and B. S. Manjunath, 2000), (Mitra Basu,2002).Research technique checks the values of edges and locations on pattern. Fabric patterns have a symmetric and periodic structure and defects generates distortions on patterns (Abdel Salam MALEK, 2012). Filter analyse the colour, texture structures or their combinations to identify the character of pixels that is defect, hole or texture yarn and obtain features in both time and frequency domains that facilitate characterizing of patterns provide useful information(Abdel Salam MALEK,2012).

This chapter is organized as follows: firstly give information about some properties and algorithms of a Gaussian functions and Multivariate Gaussian distributions in section 4.2, section 4.3 gives background an theory of Difference of offset Gaussian (DOOG) filters and section 4.4 describe the Fabric defect detection system of research and the last part is summary in section4.5.

4.2 Theory of DOOG Filters

In this section the theory and background of difference of offset Gaussian filters can reviewed. Gaussian functions are also examined for better understanding of DOOG filter, because DOOG filters are based on Gaussian function. DOOG filters are explored in 1985 by Richard A. YOUNG (Richard A. YOUNG,2001). First at all,theory and properties of Gaussian functions will be reviewed in section 4.2.1. In section 4.2.2 Multivariate Gaussian Distributions are introduced which is another way to design Gaussian function. After that section,background, theory of DOOG filterwill be examined.

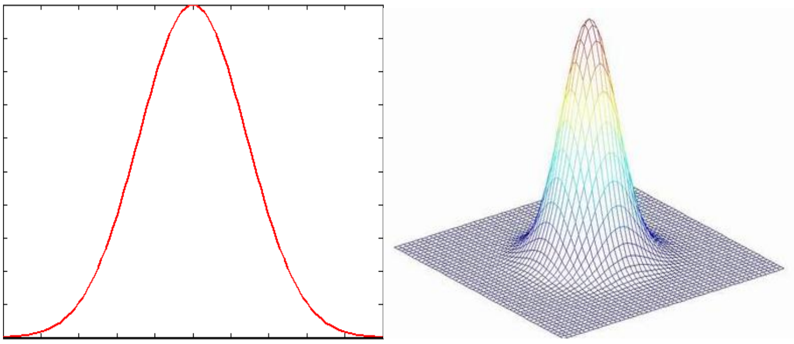
4.2.1 Gaussian Function

Gaussian functions operate in many processes in mathematics, science, and engineering, etc. Also Gaussian functions are used in image and signal processing. For example, they are used for reducing the noise that is called as Gaussian blur in signal processing. Gaussian function based filters are used to give no overshoot to a step function input while minimizing the rise and fall time.Gaussian filters have a simple structure which is described as

$$g(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{x^2}{2\sigma^2}} \tag{4.1}$$

Where x is along a directional axis and σ shows the standard deviation of filter, The Gaussian function in two dimensional coordinates (x, y), x is the horizontal and y is the vertical axis, is represented as:

$$g(x,y) = \frac{1}{2\pi\sigma^2} e^{-\left(\frac{x^2+y^2}{2\sigma^2}\right)} \tag{4.2}$$



(a) (b)

Figure 4.1 One dimensional Gaussian function at (a), and two dimensional Gaussian function at fig (b).

Gaussian functions have many properties because of their various physical and probabilistic structures (Carlo Tomasi, 2000).Only useful properties which help to design better filters, can be examined. Gaussian function is designed as proper symmetric structure that seems as cone(Guo, H.,2011).This property reduce the blurring and also the noise effect can be reduced.

Smoothness is the other useful property of the Gaussian function. The aim of smoothing is to reduce the noise effect and the sharpness in image. Gaussian Smoothing operations are applied to image by using convolution. Two dimension images and Gaussian function are shown as matrixes which have x and y components. The Gaussian function based filters and image are convolved in frequency domain. Then the pixel values can be replaced with local averaging values. So, these averaging operations reduce the level of noise on image. Another important property is that every pixel must be non-zero. Since each pixel can contribute calculations, then all pixels have values that are also essential for edge detector.

Gaussian also has separation property. When the Gaussian function is applied to image as two independent one dimensional function which means one-dimensional Gaussian matrices can apply image at horizontal and the other Gaussian matrix applied image at vertical dimensions that provide a convenience for processing and calculations. A Gaussian function can separate two dimensional functions as,

$$g(x, y) = g(x)g(y) \quad (4.3)$$

In Gaussian equation the separations is like:

$$e^{x+y} = e^{x}e^{y} \quad (4.4)$$

Horizontal-dimensional Gaussian function is:

$$g(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{x^2}{2\sigma^2}} \quad (4.5)$$

Vertical-dimensional Gaussian function is:

$$g(y) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{y^2}{2\sigma^2}} \quad (4.6)$$

The normal convolution process that filters applied to image I(m,n) is

$$c(x, y) = \sum_{x=-n}^{n} \sum_{y=-n}^{n} g(x, y) i(m - x, n - y) \quad (4.7)$$

Since two dimensional Gaussian functions are separated into two one dimensional functions, the convolution can also be split in two one dimensional processes that shown as:

$$c(x, y) = \sum_{x=-n}^{n} g(x) \sum_{y=-n}^{n} g(y) i(m - x, n - y) \quad (4.8)$$

The separated convolution reduces the number of multiplication process. So, more rapid and exact results can be obtained. The proof is, there are (2n+1) pixels in a row or column in Gaussian function that shows $(2n+1)^2$ multiplication and $(2n+1)^2$-1 summations done in convolution process. However, one dimensional convolution makes only (2n+1) multiplication and (2n) summations.

The Gaussian function is often used in pattern recognition, segmentation and special image processing operations due to their properties and structure. Especially, the smoothing and separations are useful properties; separating increase the processing speed and smoothing reduce the noise effect. Progressing speed is very important for image processing operations. Gaussian and images sizes are enlarged so the computations are raised at the same rate also the system speed is reduced in inversely proportional. The convolution process can be accelerated because of the separation property of Gaussian so the systems speed is also raised. Beside this, smoothing property decreases the noise effects. Noises cause information polluted, so the systems cannot get the desired learning from inputs. However after the smoothing the inputs become more helpful. Also a statistic type of Gaussian function can be described in 4.2.2 which named as multivariate Gaussiandistribution, it is more useful algorithm to design Gaussian function. In this research use Difference of offset Gaussian filters (DOOG)is used for characterizing the patterns.These filters are based on Gaussian functions.Therefore, they have the same properties with Gaussian function. These properties add very important characteristic qualities to our fabric defect detection system.

4.2.2 The Multivariate Gaussian Distribution

Multivariate Gaussian Distribution (MGD) is the other way to design Gaussian functions by using statistical approaches. MGD is the extended form of single variety Gaussian distribution that is the name of Gaussian function in statistic (Chuong B. Do, 2008). Let the random variables vector be X=(X_1, X_2, X_3, X_4, X_5,…,X_p).The multivariate normal distribution is an algorithm that cluster random variables around a mean value and it is given by equation 4.9

$$p(x_n) = \frac{1}{(2\pi)^{N/2}|\Sigma|^{1/2}} \exp\left(-\frac{1}{2}(x-\mu)^T\Sigma^{-1}(x-\mu)\right) \quad (4.9)$$

The parameters μ denotes mean and ^{T} symbol describes matrix transposition. $\mu \in R^N$ and isdefined as (Grimmett and Stirzaker, 1992):

$$\mu = E(x) \tag{4.10}$$

Covariance matrix is important for describing the multi various Gaussian distribution. The covariance of random variables X

$$(Cov(X) = E\left((X - \mu)(X - \mu)^T\right) = E[XX^T] - \mu\mu^T \tag{4.11}$$

The equation 4.11 can also be written as

$$(Cov(X) = E[XX^T] - E[X]E[X]^T \tag{4.12}$$

The Images is represented in I(x,y) in two dimensional space with two variables. Therefore, filters should be two dimensional. As a reason of this,multivariate Gaussian distribution represented by X_1 and X_2 random variables in matrix X. X_1 has (μ_1, σ_1) and X_2 has (μ_2,σ_2) parameters also the number of variables determine the value of N=2, and the paramaters are show as below

$$X = \begin{bmatrix} X_1 \\ X_2 \end{bmatrix} \tag{4.13}$$

$$\mu = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} \tag{4.14}$$

$$\Sigma = \begin{bmatrix} \sigma_1^2 & 0 \\ 0 & \sigma_2^2 \end{bmatrix} \tag{4.15}$$

The Σ is a diagonal matrice so the inverse operator $\Sigma^{-1}$is represented as:

$$\Sigma^{-1} = \begin{bmatrix} \frac{1}{\sigma_1^2} & 0 \\ 0 & \frac{1}{\sigma_2^2} \end{bmatrix} \tag{4.16}$$

$$p(x_1, X_2) = \frac{1}{(2\pi)^{2/2}|\Sigma|^{1/2}} \exp\left(-\frac{1}{2}(x - \mu)^T \Sigma^{-1} (x - \mu)\right) \quad (4.17)$$

$$p(X_1, X_2) = \frac{1}{(2\pi)^{2/2}|\Sigma|^{1/2}} \exp\left(-\frac{1}{2}(X_1 - \mu_1, X_2 - \mu_2)\begin{bmatrix} \frac{1}{\sigma_1^2} & 0 \\ 0 & \frac{1}{\sigma_2^2} \end{bmatrix}\begin{pmatrix} X_1 - \mu_1 \\ X_2 - \mu_2 \end{pmatrix}\right) \quad (4.18)$$

The equation 4.18 shows the representation of create a 2D Gaussian function with statistical techniques. The advantage of this method is that two parameters are enough to create the Gaussian functions. In this research, this research's Gaussian functions that use that DOOG filter are also created with this method.

4.3 Difference of Offset Gaussian (DOOG) Filters

In this section, difference of offset Gaussian filters will be described.

4.3.1 Background of DOOG Filters

The Difference of offset Gaussian in short DOOG filters first named in Young's research in 1985 and 1986 (Richard A. YOUNG,2001). According to these studies, DOOG filters are mathematically represented as the discrete form of continuous Gaussian derivatives (GD).So, DOOG and GD functions are equivalent (Richard A. YOUNG,2001). The difference between DOOG and GD is that offset parameter change the shape of DOOG filter and filter becomes an asymmetric structure but GDsare always presented in symmetric form.Therefore, the DOOG filter becomes tenderer to process all the differentiations on patterns or shapes (Richard A. YOUNG,2001), (Wei-Ying Ma,2000).

Before Young R.A. explore DOOG filters, Macleod's two researches working on development of machine vision in seventies use some filter that is similar to DOOG filters. Also similar filters were used for introducing psychophysical data by Macleod and Rosenfeld (1974), (Richard A. YOUNG,2001). Shortly before DOOG is named, they were used in cat simple cell receptive field's research by Heggelund (Richard A. YOUNG,2001). After this study, Young used filters to modelled simple cells that are called as DOOG filters (Richard A. YOUNG,2001). Livingstone (1998) and De Valois *et al.* (2000) used wiring modelling technique to model the primate simple cells. These wiring models designed with developing spatio-temporal receptive field shapes that the structures are closely matched with a DOOG spatio-temporal model. The successful modelling outputs of these filters enhance their confidence in physiological mechanism researches.

At first, DOOG filters were used in biological or physiological researches.The conclusion is that the DOOG filter is very successful in modelling shapes. After its representation, new techniques and researches began to use DOOG filter as a parts of their research. S. Srisuk use DOOG filter for estimating the direction of edges in his edge flow technique (Sanun Srisuk, 2002). A research which normalized cuts technique use for segmentation objects from pattern use that filters to analyse the pattern and the obtained features. These features create the energy spectrums of patterns in which object gets high frequency values than background pattern.

All these researches show that the DOOG filters has a success in modelling and patterns characterizing. Fabric Defect detection systems have a similar logic with these researches. Defects create some abnormal differentiations on fabric pattern. Identification of these defects is related with a better pattern characterization.

4.3.2 Theory of DOOG Filters

Previous researches show that DOOG filters are good in texture segmentation. Fabric, that explained before, are created after a weft threads and wrap threads weave with a knitting plan. Also the fabric thread structures may be bigger or smaller. It is harder to perceive the defects If thread texture plan becomes smaller, in parallel also the defects has small regions that hard to detect without extra process. Therefore, better texture characterization and segmentation must be done for catching all the textural information .This research use difference of offset Gaussian filter DOOG filter for texture characterization and segmentation process. Also the algorithmic simplicity, rapid design and implementation properties are the other reasons to choose this filter.

DOOG filters are designed by using Gaussian functions. As its name suggests, theoretical description of DOOG filter is, difference of designed Gaussian functions with an offset value. Offset value is the distance between two Gaussian kernels(Wei-Ying Ma, 1998).DOOG filter also explained in a different definition. Young (1985) explain that the derivative of a Gaussian function is mathematically closely equal to discrete difference between Gaussian function with vanishingly small offset distance (Richard A. YOUNG,2001).It can be easily designed because of their simple structure that is:

$$DOOG_{\sigma}(x) = G_{\sigma}(x) - G_{\sigma}(x+d)(4.19)$$

Where d is the offset value that shows the distance between two Gaussian functions. Also the Gaussian derivative functions are represented as

$$g_n(x) = \frac{d^n}{dx^n} g_0(x)(4.20)$$

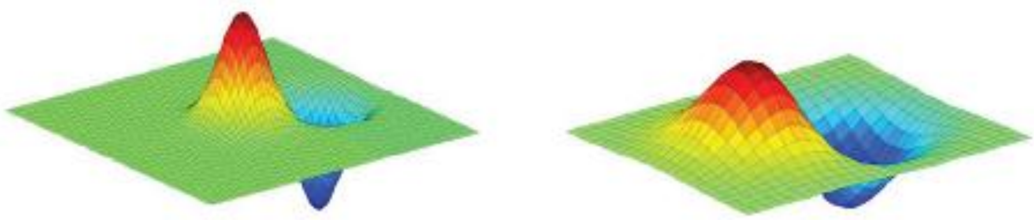
g_0 shows the Gaussian function that also shown in equation 4.20 and x denotes the horizontal axis.If we compare the first two steps of derivation of Gaussian and DOOG filter (Richard A. YOUNG,2001).

$$g_1(x) = -xg_0(x)(4.21)$$
$$g_2(x) = (x^2-1)g_0(x)(4.22)$$

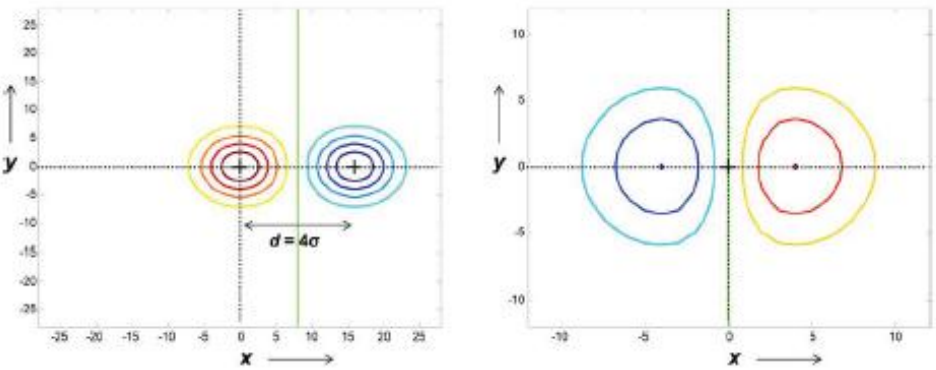
And DOOGs are

$$g_0(x) = DOOG_0 = g(x)(4.24)$$
$$g_1(x) \simeq DOOG_1 = g(x) - g(x+d)(4.25)$$

The important case is that an offset value of DOOG filters offset values d may be smaller to resemble to Gaussian derivative. The similarities of these two methods are shown in experimental results that all the three stage DOOG filters can be plotted. However, the difference between DOOG and DG is that the former is asymmetric whereas the latter one is a symmetric operator. This property of DOOG, unlike DG, makes it sensitive to the directions θ and θ+π, as shown in the contour plots in Fig. 4.2 (c) and (d) (P. Ghosh, L. Bertelli, B. Sumengen, B. S. Manjunath, 2010).



(a) (b)



(c) (d)

Fig.4.2. This figure demonstrates the difference between the Difference of offset Gaussian (DOOG) and the first derivative of Gaussian (DG), (a) The surface plots of DOOG, (b)(c) and (d) gives the corresponding contour plots, respectively. The offset (d=4σ) of DOOG is shown by a black arrow in the contour plot (bottom left). It is to be noted that DOOG is an asymmetric operator unlike DG which is symmetric.

4.4 FDDS Based on DOOG filter with Histogram Analysis

The research is about detection of fabric defects. Defected or non-defected fabric must be characterized in most accurate way. However, defects have different coordinates, shapes and directions that cause difficulty in fabric pattern analysis. So far various types of FDDS have been used in textile industry to find the defects. In this study first time DOOG filters with histogram analysis have been proposed to find the defects in FDDS. The proposed FDDS consist of four section; Pre-processing, DOOG-filter design, post processing and classification. In the following sections each will be described.Figure (4.3) presents the flow-chart of proposed FDDS.

Our fabric defect detection System includes two different properties to solve above described problems. The first one is to use two different DOOG filtersfor detecting process. Filters are used for increasing the efficiency of detection process. One filter can cause to lose the detailed information but if two filters to use work together, it decreases the probability of missing. The second property is to use a multi parameter blocks in designing process. A block parameter sets entered to the system so the filters are designed at each parameter. After that, all filters can apply to fabrics then results can be compared to decide the best filter and features. Also the two properties examined in detail in this section. The first thing to do in pre-process is to assign the parameters of filters.

4.4.1. Parameter

There are five parameters to design the filters. Two Standard deviation parameters in horizontal and vertical direction, size of the filter, orientation and offset value.

4.4.1.1 Standard Deviation ($\sigma_{x,}$ σ_y)

This is the most important parameters to design the filters. Standard deviation is a parameter which set the width of filters. Standard deviation decreases effects of filter as filters become tighter and increases to expand the effects of filters. Two standard

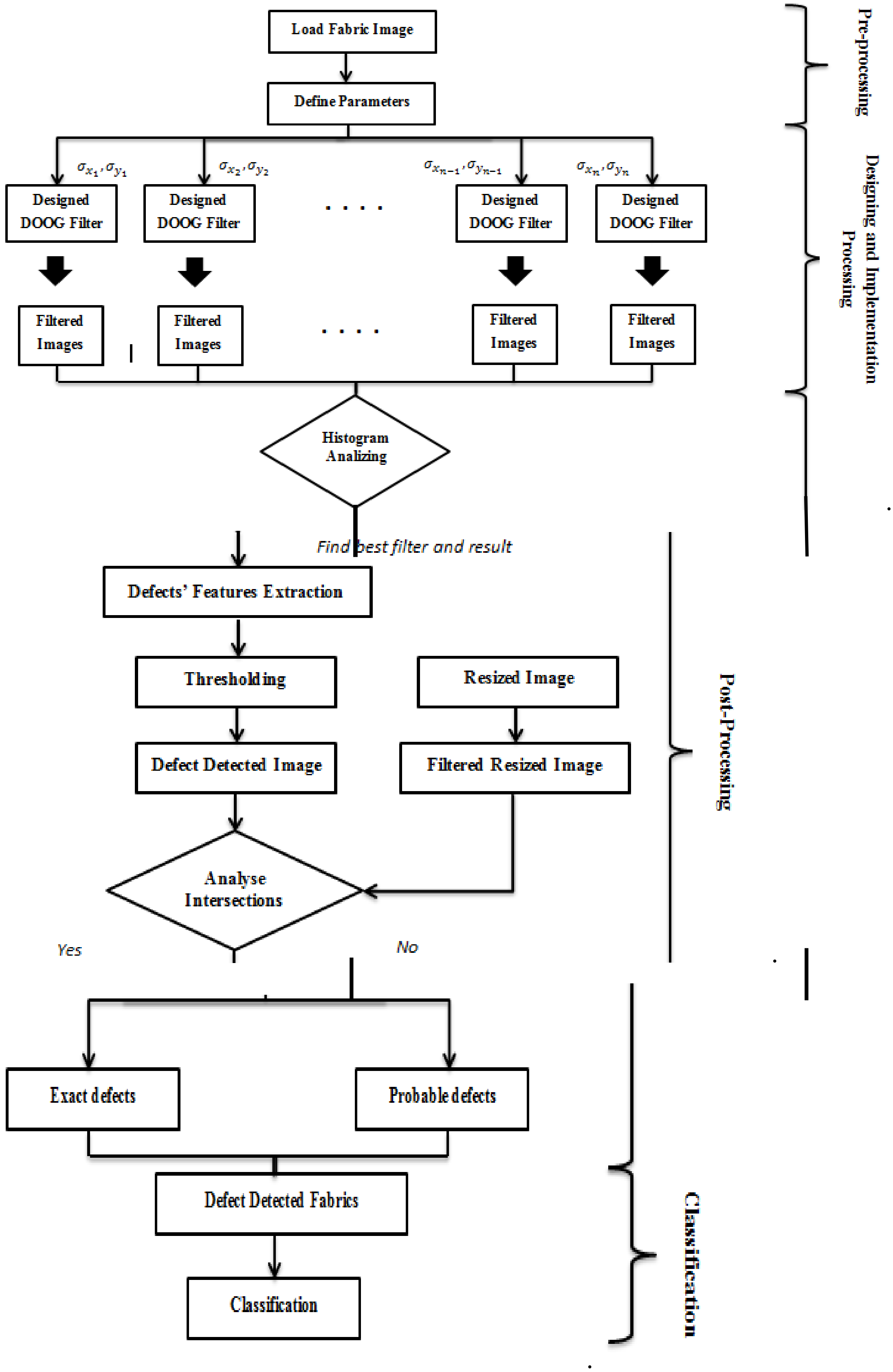
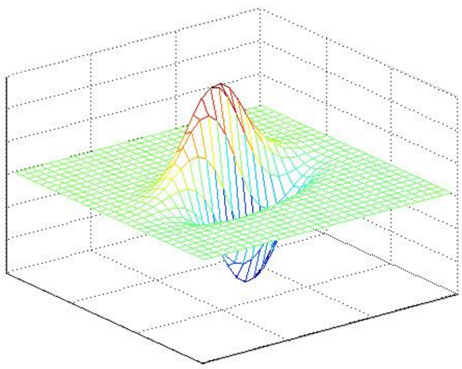
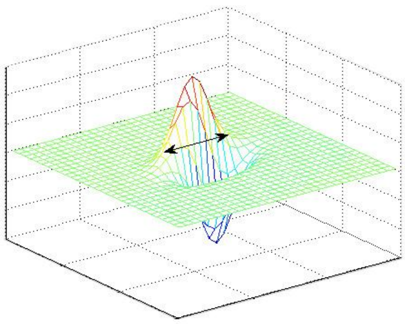


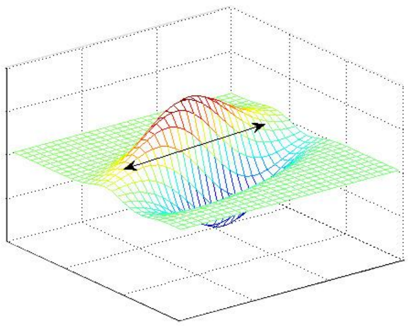
Figure 4.3 Flow-chart of proposed FDDS.

deviation parameters provide to control the designing of filters in horizontal and vertical directions as σ_x and σ_y respectively. The effects of standard deviations on filters are shown in figure 4.3. Because of different shapes and dimensions of defects, it is not enough to assigning a single constant value to standard deviation .So a set of data $\sigma_{x=(}\ \sigma_{x1}, \sigma_{x2}, \sigma_{x3}, \sigma_{x4}\ ,\dots\ ,\sigma_{xn)}$ and$\sigma_{y=(}\ \sigma_{y1}, \sigma_{y2}, \sigma_{y3}, \sigma_{y4}\ ,\dots\ ,\sigma_{yn)}$ are assigned and each parameters generate a form to create a filter. These properties also increase the efficiency of detecting process.



(a)





(b) (c)

Figure 4.4 (a) DOOG filter with three different σ_x andσ_y values; (a), (b), and(c).

4.4.1.2 Size of filter

Size parameter determines the dimensions of filter grid. Designed filters are created on these grids. The size is significant because if the grid is not big enough the filters overflow from grid so the significant properties of filter cannot be used. Filters are in 2D structures as (x,y) so the grid must be also two dimensional. But system use size parameter that set both of x and y axis length and consist a square grid in (size, size) dimensions.

4.4.1.3 Orientation, θ

Orientation parameters determine the rotation angles of filter on grid. As explained before, defects have different shapes, dimensions and directions. The filters can easily define defects that are aligned with filter direction.Therefore, filters ought to be routed to identify all various defects occurring in different angles. Θ represents the filter angle value, and x' and y' gives the equation of rotated in x and y directions respectively.

$$DOOG_{\sigma,\theta}(x,y) = DOOG_{\sigma}(\mathrm{x}',\mathrm{y}') \quad (4.28)$$

$$DOOG_{\sigma,\theta}\left((x',\mathrm{y}')\right) = G_{\sigma}(x',\mathrm{y}') - G_{\sigma}(x'+\mathrm{d},\mathrm{y}') \quad (4.29)$$

$$x' = \mathrm{x}\cos\theta - \sin\theta \quad (4.30)$$

$$y' = \mathrm{x}\sin\theta + \mathrm{y}\cos\theta \quad (4.31)$$

But in studies the orientation values and added to the image as a rotation matrix

$$R = \begin{bmatrix}\cos\theta & -\sin\theta \\ \sin\theta & \cos\theta\end{bmatrix} \quad (4.32)$$

Hence, the new coordinates can be obtained by the equation

$$\begin{bmatrix}x' \\ y'\end{bmatrix} = R * \begin{bmatrix}x \\ y\end{bmatrix} \quad (4.33)$$

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} x\cos\theta - y\sin\theta \\ x\sin\theta + y\cos\theta \end{bmatrix} \quad (4.34)$$

4.4.2 Designing and Implementation Processing

Here, filter design and its implementation will be separately described.

4.4.2.1 Filter Design

Filters are created with various parameters by software program. This stage creates two DOOG filters; one is the $DOOG_1$ filter and negative $DOOG_2$filter. In first step multivariate Gaussian distribution is used for creating Gaussian functions because it require only two parameters to create filters,also it faster than other methods .The Multivariate Gaussian Distribution obtain the Gaussian function. If section 4.2.2 is examined it is seen that filter has two dimensional structure with using X_1 andX_2 as input variables, μ_1, μ_2 means, and$\sigma 1$, σ_2 as standard deviations. The multivariate Gaussian distribution is given as

$$p(x_n) = \frac{1}{(2\pi)^{N/2}|\Sigma|^{1/2}} \exp\left(-\frac{1}{2}(x-\mu)^T\Sigma^{-1}(x-\mu)\right) \quad (4.35)$$

But the filters also have an orientation variable that provides the rotation on grid. Rotation matrix is symbolized by O. The rotation of X_1 and X_2 create dependencies. İf we accept σ_2 very small value, and $\sigma 1$ very huge number, and then X takes close values to horizontal axis. So the distribution of X which rotate with O matrix is close to y=x line on coordination system. The relation is shown as y=O.x (David Jacobs,2005).

$$Y = f(x) \qquad p(y) = p(x)\left|\frac{d_x}{d_y}\right| = p(f^{-1}(y))\left|\frac{df^{-1}(y)}{dy}\right| \quad (4.36)$$

Now x= $O^T y$ is a description to incorporate it with multivariate Gaussian distribution as below.

$$p(y) = p\big(x(y)\big) = \frac{1}{(2\pi)^{\frac{2}{2}}|\Sigma|^{\frac{1}{2}}} e - \frac{(O^t y-\mu)^T \Sigma^{-1}(O^T y-\mu)}{2} = \text{(4.37)}$$

$$\frac{1}{(2\pi)^{\frac{2}{2}} 1. |\Sigma|^{\frac{1}{2}}. 1} e - \frac{(y - O\mu)^T U \Sigma^{-1} O^T (y - O\mu)}{2} =$$

$$\frac{1}{(2\pi)^{\frac{2}{2}} |O|^{1/2}. |\Sigma|^{\frac{1}{2}}. |O^T|^{1/2}} e - \frac{\big(y - \mu_y\big)^T ((O^T)^{-1} \Sigma O^{-1})^{-1} \big(y - O\mu_y\big)}{2} =$$

$$\frac{1}{(2\pi)^{\frac{2}{2}} |O \Sigma O^T|^{\frac{1}{2}}} e - \frac{\big(y - \mu_y\big)^T (O\Sigma O^T)^{-1} \big(y - O\mu_y\big)}{2} =$$

$$\frac{1}{(2\pi)^{\frac{2}{2}} |\Sigma|^{1/2}} e - \frac{\big(y - \mu_y\big)^T {\Sigma_y}^{-1} \big(y - O\mu_y\big)}{2}$$

Where $\mu_y = O\mu$is the expectation of y and $\Sigma_y = O\Sigma O^T$ is the covariance matrix of y. Also the offset parameter has to be included. It uses to change the coordinates of mean. The First Gaussian is always located on centre that has [0,0], the other Gaussians' centre is shifted by the given offset value.

$$\mu_{offset} = A\, x\, \mu_2 \text{(4.38)}$$

A is the amplitude of offset parameter and μ_2 is the standard deviation in vertical axis. So the filters include all the required parameters of our research. Then Gaussian distributions can be obtained as shown in figure 4.4. Differentiation is the last part of designing filters.

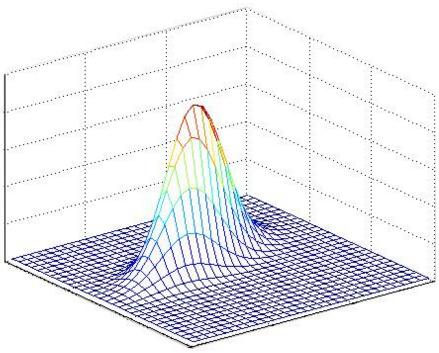
$$p(y) = \frac{1}{(2\pi)^{\frac{2}{2}} |\Sigma|^{1/2}} e - \frac{\big(y-\mu_y\big)^T {\Sigma_y}^{-1} \big(y - O\mu_y\big)}{2} \text{(4.39)}$$

4.4.2.2 Implementation of filters

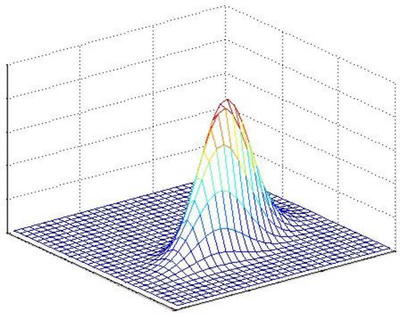
Convolution is a mathematical operation and in short explanation, it is multiplication of input data by filter or masks coefficients (David Jacobs, 2005). The Convolution are used in several applications; image fitting, signal or image filtering, feature extraction, mathematic operations, etc..both in time and frequency domains. h(t) represent convolution in time domain and H(f) represents the convolution in frequency domain. The convolution of two function x(t) and h(t) is represented as;

$$x * h \Longleftrightarrow X(f)H(f) \quad (4.40)$$

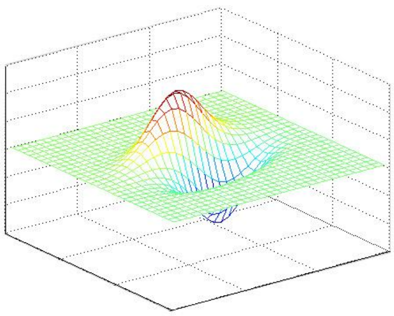
$$x * h = \int_{-\infty}^{\infty} x(\tau)h(t-\tau)\, d\tau \quad (4.41)$$



(a)



(b)



(c)

Figure 4.5 (a) Gaussian function with (0,0) offset value, (b) Gaussian function with offset value of (1/2. σ_x) (c) DOOG filter obtained by Gaussian function given in (a) and (b).

As might be expected X(f) and H(f) are the frequency domain representations of function s(t) and h(t). Images are described in discrete forms(William H. Press,Saul A. Teukolsky, William T. Vetterling, Brian P. Flannery, 1988).

$$y[k] = \sum_{0}^{N-1} x(m-k)h(k) \quad (4.42)$$

Equation 4.44 is the convolution obtained for image processing from equation 4.42;

$$x[m] * h[m] = \sum_{k=0}^{N-1} x[k]h[m-k] \quad (4.43)$$

$$= \sum_{k=0}^{N-1} [\frac{1}{N}\sum_{n=0}^{N-1} X[n]e^{-i2\pi kn/N}]\ [\frac{1}{N}\sum_{l=0}^{N-1} H[l]e^{-i2\pi(m-k)l/N}]$$

$$= \frac{1}{N}\sum_{n=0}^{N-1} X[n] \sum_{l=0}^{N-1} H[l] \frac{1}{N}\sum_{k=0}^{N-1} e^{-i2\pi(m-k)l/N}$$

$$= \frac{1}{N}\sum_{n=0}^{N-1} X[n] \sum_{l=0}^{N-1} H[l]e^{-i2\pi ml/N} \frac{1}{N}\sum_{k=0}^{N-1} e^{-i2\pi k(n-l)/N}$$

$$= \frac{1}{N}\sum_{n=0}^{N-1} X[n] \sum_{l=0}^{N-1} H[l]e^{-i2\pi ml/N}\ \delta[n-l]$$

$$= \frac{1}{N}\sum_{n=0}^{N-1} [X[n]H[n]]e^{-i2\pi mn/N}$$

$$F\big[x[m] * h[m]\big] = \sum_{m=0}^{N-1} [x[m] * y[m]]e^{-i2\pi mn/N} = X[n].H[n] \quad (4.44)$$

Where X[n] and H[n] is the transform of corresponding signal.

Discrete convolution is used for different situations but in our research, there are many fabric images with wide dimensions. So it requires many and long calculations. However, calculation can be done speedy with Fast Fourier Transform (FFT).

*4.4.2.2.1 Fast Fourier Transform (FFT).*There are different ways to compute the Discrete Fourier Transform (DFT), for example simultaneous linear equations or correlations, etc. (William H. Press,Saul A. Teukolsky, William T. Vetterling, Brian P. Flannery,1988).Computation of DFT is to slow. Fast Fourier transform is also a method to compute Discrete Fourier transforms with same result as evaluating in DFT definition and the fast computation time is the advantage of this method. The FFT is defined as;

$$X_k = \sum_{n=0}^{N-1} x_n \, e^{-i2\pi k\frac{n}{N}} \qquad k = 0, \dots, N-1 \quad (4.45)$$

Let x_0,$x_{1,\dots,}$ x_{N-1} be complex numbers. For evaluate the speed of FFT. The normal distribution of DFT requires O.(N^2) operation(Matteo Frigo, Steven G. Johnson,2005).O is shown the maximum bounding value and N is the number of x_k required a sum of N terms. If the same operation done with Fast Fourier Transform, it use O (N log N) operation is enough.

Fabric Images are two dimensional textures so 2D FFT is applied to convolve the image with filters. For simplicity instead of convolution; calculations image f(x,y) and filter s(t,u) are transformed frequency domain, and multiply them and calculate the inverse FFT to turn into time domain. 2D FFT is same with Discrete Fourier transformthat is extended in two directions (Steven W. Smith,1997).For the image f(x,y), its 2D FFT F(u,v) can be found using formula

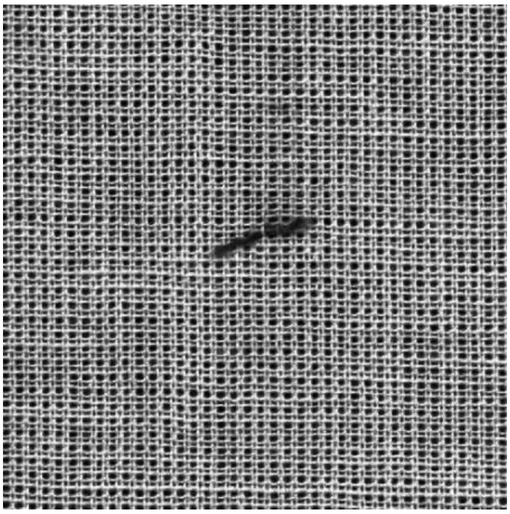
$$F(i,j) = \sum_{a=0}^{M} \sum_{b=0}^{N} f(x,y) e^{-j2\pi(\frac{ix}{M}+\frac{jy}{N})} \quad (4.46)$$

$$S(i,j) = \sum_{a=0}^{M} \sum_{b=0}^{N} s(x,y) e^{-j2\pi(\frac{ix}{M}+\frac{jy}{N})} \quad (4.47)$$

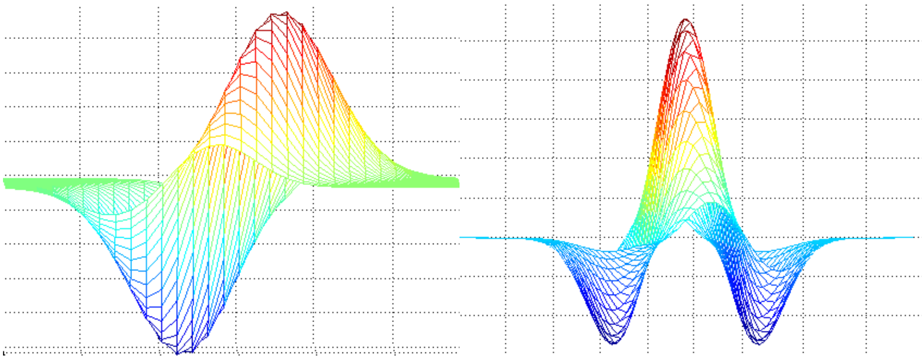
The inverse transform can be obtained using the formula

$$f(x,y) = \sum_{a=0}^{M} \sum_{b=0}^{N} F(i,j) e^{-j2\pi(\frac{ix}{M}+\frac{jy}{N})} \quad (4.47)$$

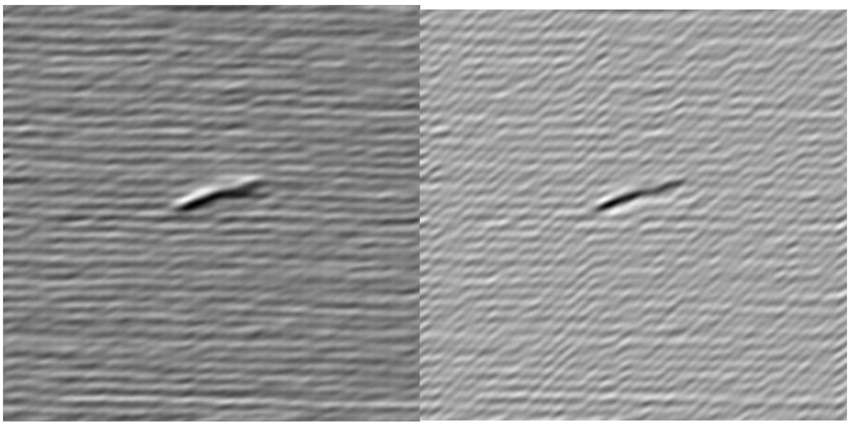
Fabric images and filters and their convolution process are shown in figure 4.5.



(a)



(b)(c)



(d)(e)

Figure 4.6 Show the convolution processes (a) is the original image(b) and (c) show DOOG filters(d) Results of convolution for $DOOG_1$ and (e) Result of negative $DOOG_2$.

4.4.3. Post- processing

Further analyse of the filter results are also necessary for segmentation. The aim of this process is to find the best output energy map. At the end of design and implementation process, all the filter output is stored for analysing.

Filters are designed to create high energy responses to detect any distortions on fabric patterns. Filters give high responses for images with aligned direction and spread value which is similar to the defect size, but gives small responses for the others. Here further processing is required through a histogram calculation obtained from filter outputs. Firstly, output energy maps are shifted to the range 0 to 1.

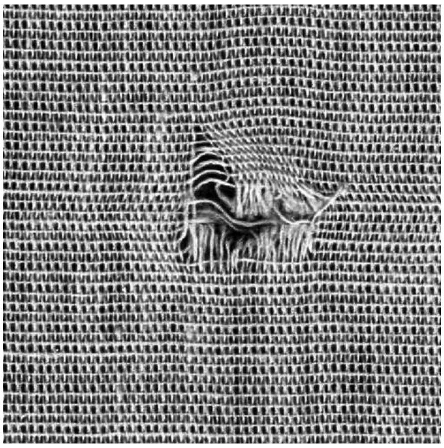
$$SM(x,y)_n = M(x,y)_n - min_n \quad (4.48)$$

$$CM(x,y)_n = \frac{M(x,y)_n}{max_n} \quad (4.49)$$

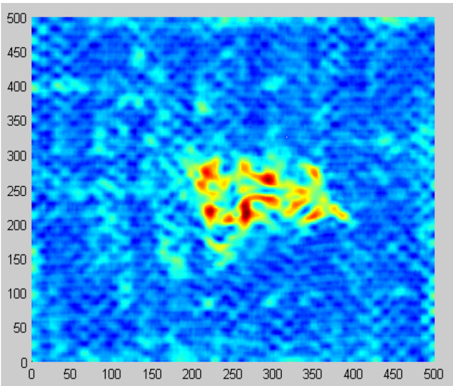
SM and CM denote the shifted maps and compressed maps, respectively, M(x,y) is the energy map,max and min show the maximum and minimum of maps and the n shows the number of map. After the data are prepared, system determines the histograms of fabric’s energy maps. Histograms show visual impression of the distribution of data. For example, afabric image is shown with its filtered result and its histogram.

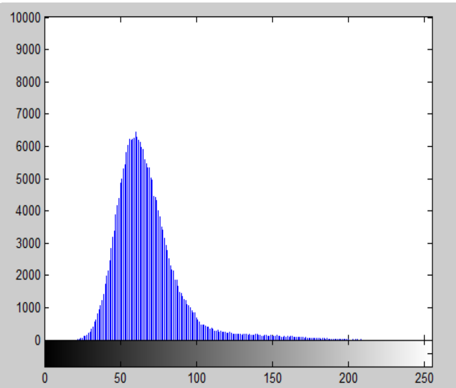
As shown in the figure, non-defected energy responses are close to the mean of energies but the defected energy responses disrupt the order and move away from the mean. This feature allows us to find the defected areas. But, we should separate the defect and non-defect areas. Therefore, the non-defected fabric patterns are separated with a triangle. The outside of the triangle can be considered as defected corresponding pixels. The triangle can be designed with an analytical equation. Since histograms take different shapes the triangle has to be adaptively calculated. To calculate the triangle; we take three points for each side of the histogram. The points are the middle values of three sections between maximum and minimum histogram values.pixels. The triangle can be designed with an analytical equation. Since histograms take different shapes the triangle has to be adaptively calculated. To calculate the triangle; we take three points for each

side of the histogram.



(a)





(b) (c)

Figure 4.7. (a) The original image (b) The result of DOOG filter and (c) The energy histogram of the DOOG filter output for image in (a).

The points are the middle values of three sections between maximum and minimum histogram values. The two lines are draw from 1 to 3 and from 2 to 3 and new lines generatedas their average. The final lines in each side determine the bottom of the triangle. The equation 4.50 gives the calculation of the lines. Figure 4.7 shows the obtained triangle for the image given in figure 4.6.

$$y - y_1 = \frac{y_2 - y_1}{x_2 - x_1}(x - x_1) \tag{4.50}$$

Table 4.1 gives the calculation of the triangle for the image given in figure 4.6

Table 4.1 The coordinates of points that use to create an imaginary triangle.

Left points			Right points	
X1	36	832	101	703
X2	44	2496	83	2535
X3	54	5466	68	5491
		Lines		
Xline1	(X2-X1)	32	(X2-X1)	107,9072
Xline2	(X3-X1)	32.7682	(X3-X1)	105,8452
Left Line			Right Line	
32			106	

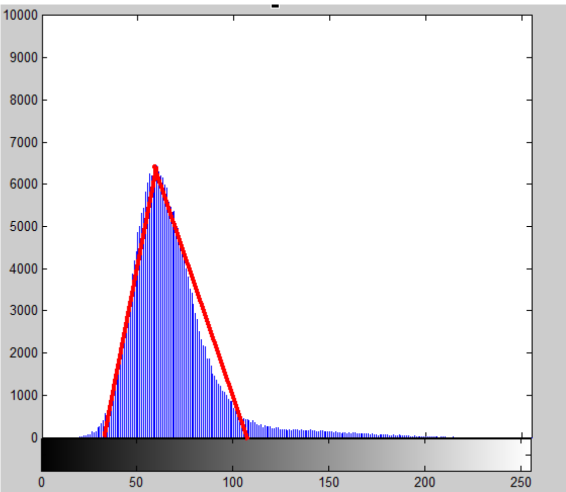


Figure 4.8 Show the lines that create the imaginary triangle.

When coordinates of triangle are defined two main features are obtained. These are; top of the histogram value and the other is the sum of the histogram values outside of the triangle. Then two tables are generated for each feature starting from highest to lowest value for all DOOG filter output. Then, a scoring is applied for each one as to give highest score for the highest value. The histogram taking the highest score for total of two features is taken as the winner to represent the best filter for the defect.

Segmentation process is used for identifying the defects. This stage is necessary since the output of the DOOG filter consist of defects and non-defects patterns. In addition, the end of defined triangle may not fully separate the defected and non-defected regions. Therefore, it is required to add a threshold parameter to the end limits of the triangle to have a better separation. In this way triangle becomes wider, and it increase the possibility of covering the defected parts. The part in the histogram out of the triangle end limits corresponds to defected parts. The experimental work has shown that threshold value of 10 is enough to separate the defected parts. The defected parts in the output of the DOOG filter is found by getting the coordinates of the energy levels of the best that is outside of the triangle of the histogram. All points outside the triangle define the complete defected parts.

In general defected parts do not have homogenous structure and therefore, defected area may not be continues. To determine the complete defected parts the pixels around the pixels of high energy values somehow connected. These pixels were combined by morphological operation imerode. After this process all defected pixels are set 255 and all others are set to 0. With this way we have black and white image to have defect separation, figure 4.8.(b).

The experimental work has shown that the parts which were found as defected may not correspond to actual defects. The reason for this false detection is the lighting effects and some fabric irregularities. To reduce these effects the image is reduced. In our work we used 100x100 new image sizes. This new image is only applied to the DOOG filter which was chosen previously as the best. Then by applying the defined thresholding the corresponding defected areas are defined and set to 255 values and set back to original image size. Now, there are two black and white images to compare. The overlapping white area corresponds to exact defect regions, figure 4.8. (d).

At this point the defects are divided into two parts as exact defects and probable defects.

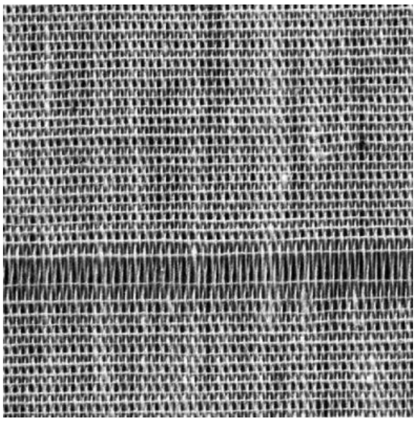
i. Exact Defects

Exact defects are the regions which consist of the intersections of output DOOG filter for the original and the reduced size image.

ii. Probable defects

Probable defects are the regions which exist only for the original image.

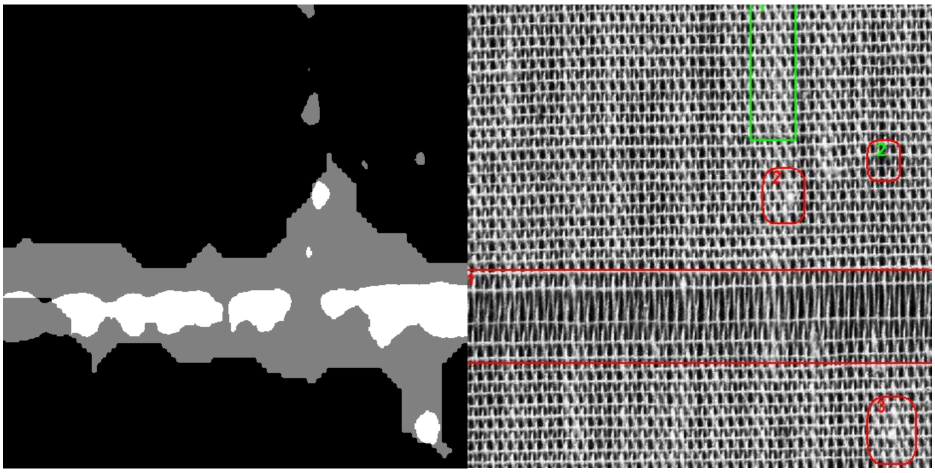
At this level, the defects on fabric patterns obtained with their location and their certainty level. This is the last step of post-processing.



(a)

(b) (c)

Figure 4.9(a)Original Image (b) Segmented DOOG filter output for original size, (c) DOOG filter output for reduced image size.



(d) (e)

Figure 4.9 (Cont)(d) overlap of segmented image of (b)and (c), (e) exact defects in red colour and probable defects in green colour boundaries.

4.4.4 Classification

Now it is necessary to classify the defects into groupsby using their structural properties. If the class or type of defect is known it is easy to find solution for the source of problem and the experts interfere the machine faster. Different methods can be used to make classification. In this research, the physical properties of the defect will be used to use for classify defects. The directions, shades and length of defects have been used as features for classification. Directions of filter shows if the defects are a weft, warp or surface defects. The horizontal defects named as weft defects and vertical defects are named as warp defects also if the defects expand in both directions it is named as a surface defect.The dimensions of the defect define whether the defects move through the whole thread length or just with limited length. The shades determine the defect is a whole or bulge. The figure 4.9 gives the flow chart for the classification of defects. The defects with similar characteristic take part within the same class. In this study the total of 10 classes used.

4.5 Proposed FDDS Graphical User Interface

Graphical User Interface is used to control the complex programs with components.Various control components, for example text, labels, and menus provide a connection between user and programs. In short, Graphical User Interface is a control screen which use visual elements.The aim of GUI's is to provide a simple and helpful interface screen. Beside this, the interface also represents a chance to use all of properties for managing programs. This is achieved by using components. Different users also use the interface programs so they must be more understandable. GUI applications can be used in various fields and all the interfaces have different characteristics which related with application's aim, demand and their representations.

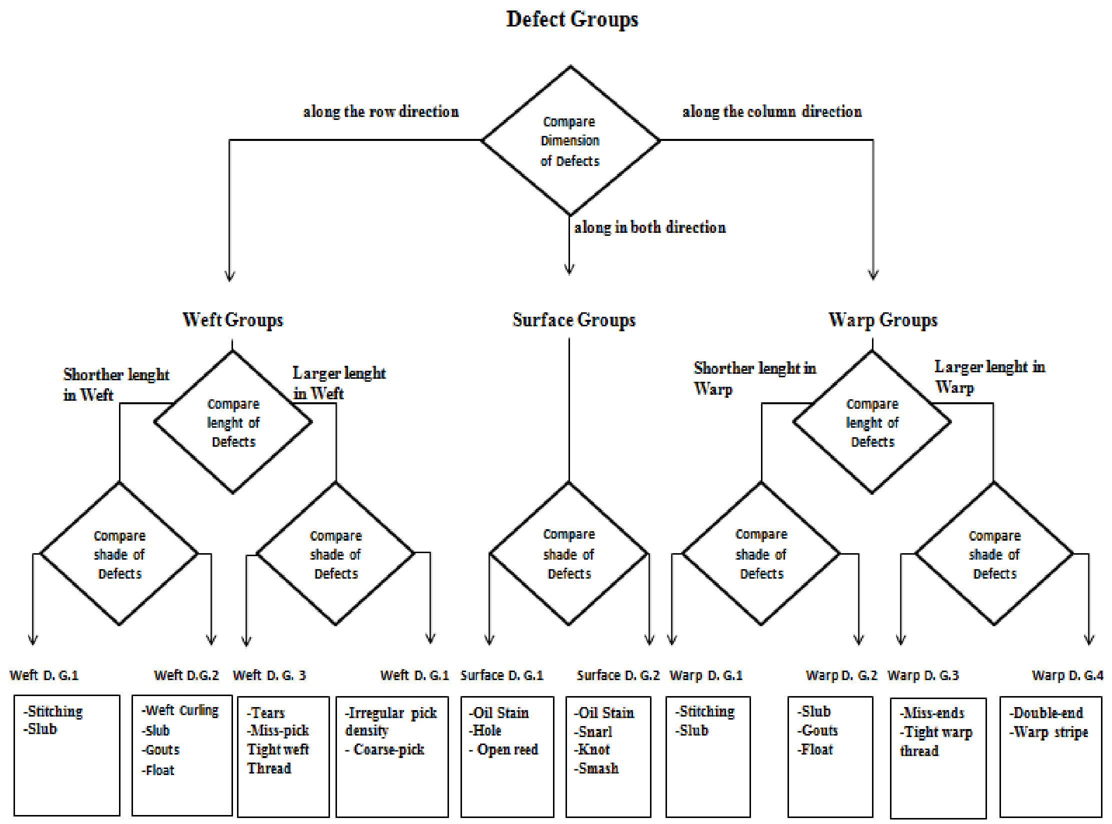


Figure 4.10 Defects Groups flow chart.

Matlab is a comprehensive image and signal processing program. Also a GUI is included for user to develop their projects. Matlab graphical user interfaces are designed by using some elements which are components, figure and call-backs.

Components are name of graphical items on components bar. Labels, lists, radio buttons, pushbuttons are the examples of components. Components use for creating connection between the user and the related part of programs.Figures are the background screen of the user interface. All the items placed on these screen.Call-backs are used to start the implementation of function .When a component becomes active the call-backs are usedto activate each program that related with activated component. If a component does not have a call-back, it becomes useless. Therefore, the components and call-backs have strong relations with each other's.GUI that designed for our FDDS is examined in section 4.5.1.

4.5.1 Fabric Defect Detection System GUI

A GUI is added to our research to simplify the usage of the programme. The GUI control the processes of research program as assign the parameters, start the processes and take the results .The FDDS's Graphical User Interface is shown in figure 5.2.

As shown in the figure 4.10 designed GUI is separate into 6 parts;process panel, parameters panel, classification panel, outputs panel, figure and grid .These parts are described in following subsections.

4.5.1.1 Processing Panel

Processing panel is used to perform image loading, and system execution. The related buttons are described in following subsections.

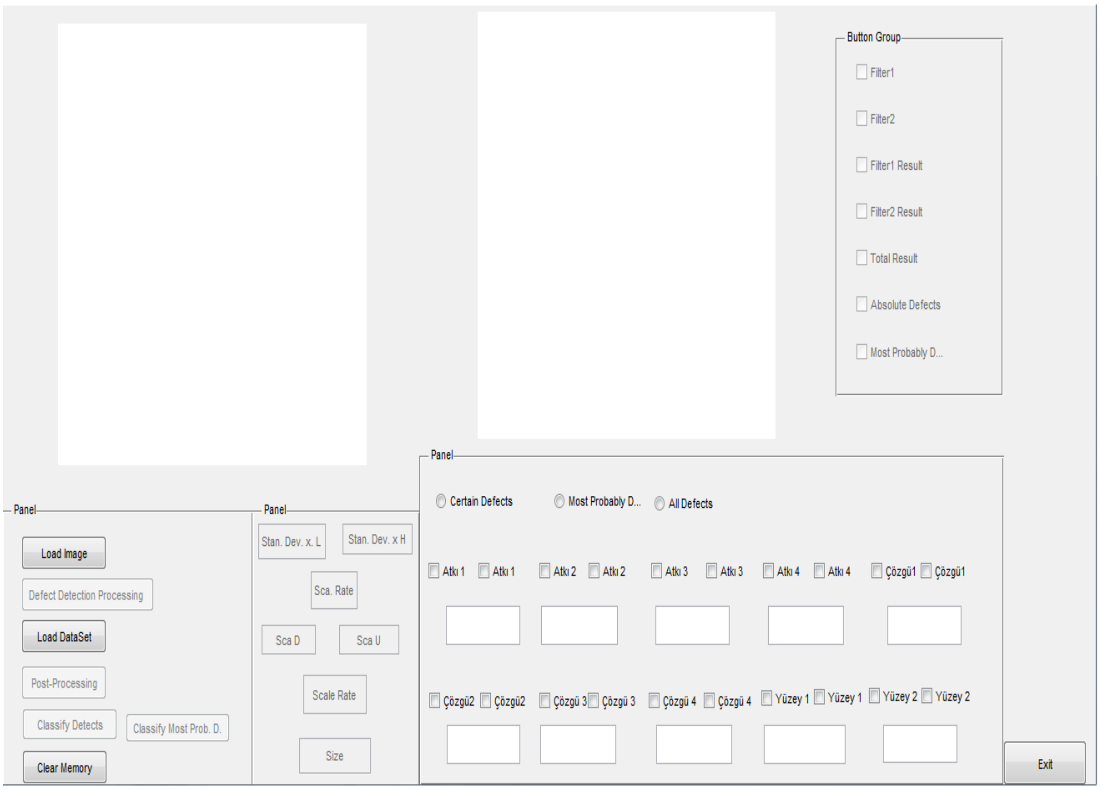


Figure 4.11 Shows the graphical user interface of FDDS

As shown in the figure 4.10 designed GUI is separate into 6 parts;process panel, parameters panel, classification panel, outputs panel, figure and grid .These parts are described in following subsections.

i. Load Image: Load image button is used to load the selected image to FDD system.

ii. Defect Detection Processing

Defect detection processing button activates the system completely following the parameter setting.

iii. Recall Data Sets

Recall Data Sets button is used to recall previously stored processed data sets.

iv. Post-Processing

Post processing button is to activate related pre-processing functions.

v. Classify Defects

This button performs the classification of the exact defects only.

vi. Classify probable defects

This buttons gets the probable defects.

vii. Clear memory

This button clears all the memory.

4.5.1.2 Parameters panel

The parameter panels use to enter the parameter values to define the standard deviation and size of filter grid. Stan.dev.x.L shows the starting point of $\sigma_x$and stan.dev.x.H shows the ending point of $\sigma_x$and Scale rate shows the scale factors which identify the value of σ_x. Also Stan dev.y.L shows the starting point of $\sigma_y$and

Stan dev.y.H shows the ending point of σ_y and scale rate shows the scale factors which identify the values of σ_y. The last parameter size is determining the value of filter grid

4.5.1.3 Classification panel

Detected defects are classified according to 10 difference classes and the shown.

4.5.1.4 Output panel

Output panel includes check boxes. The panel used to show the system outputs.

4.5.1.5 Image grid.

Image grid shows the input image and the output image with detected defects.

4.5.1.6 Data grid

Data grid informs the defect class and the subclass.

4.6 Summary

In summary, our goal is to develop a method for the accurate detection and classification of fabric defects based on the DOOG filter. Therefore some specific properties added to FDDS to increase the detection. The proposed FDDC method contains the following three major parts:

i. Parameterization of the difference of offset Gaussian filters and creation of filters with using multivariate Gaussian distributions.

ii. Post processing part isto analyse the filter results and find which filter is the best filter. Then, the histogram threshold is used as information to detect the defected regions. A new reduced image size is used to probable defects.

iii. Classification of defects according to physical properties.

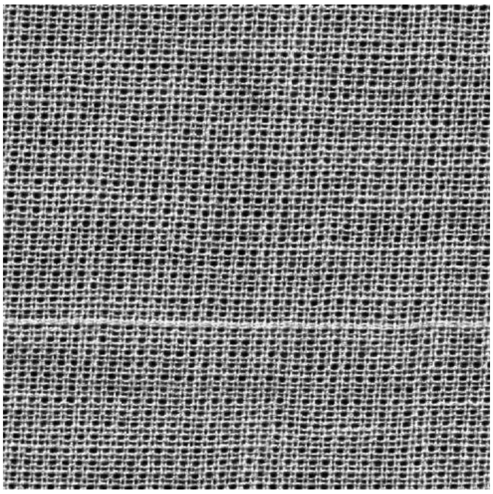
CHAPTERFIVE
RESULTS AND DISCUSSIONS

5.1 Results of Research

In this chapter we present and discuss the developed FDDS performance with various parameter set. The aim was to design an FDDS with successful detection of defects. In the developed FDDS system, there are multivariate parameters, two DOOG filters, and a special histogram analysing approach.

i. Parameters

The FDDS need four parameters to design the DOOG filter. The parameters can be entered manually from user interfaced or the system assigns the parameters automatically.The parameters are; orientation, size of filter, and standard deviations on vertical and horizontal axis. The orientation and size of filter can be entered as a single value. However the σ_x and σ_y are entered as a set of data .In figure 5.1 parameters are set as θ= [30, 60, 90,…, 360],size =30 and theσ_x and σ_y are in range of between 4 to 20 and the scale parameter is 8. The result image is the summation of all 12 DOOG filter outputs. The images show the energy levels for the corresponding pixels. As seen each image reflects different energy distributions. However, only one of them reflects the actual defects in the best way. The purpose of this illustration is to show that the performance of the system heavily depends on the system parameter selection.



(a)

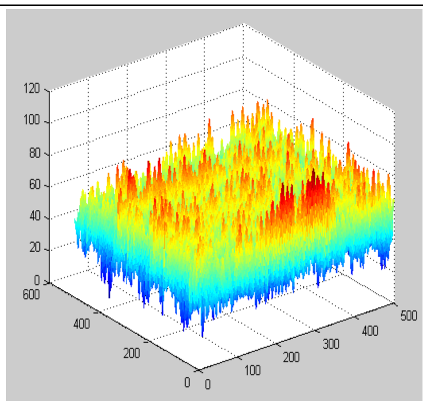
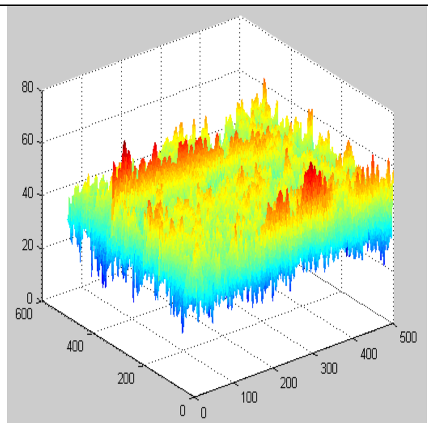
σ_x	σ_y	Size	Θ	Image
4	4	30	30,60,90,…, 360	
4	12	30	30, 60, 90,…, 360	

Figure 5.1(a) Original image (b) the filter results with different standard deviation parameters.

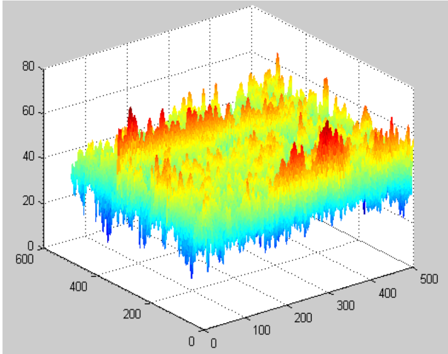
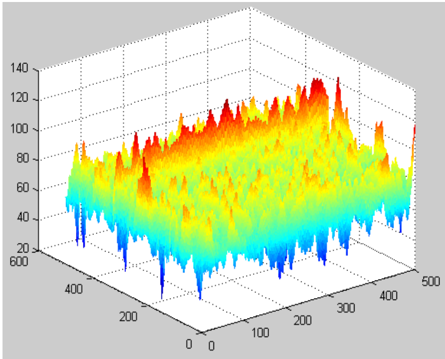
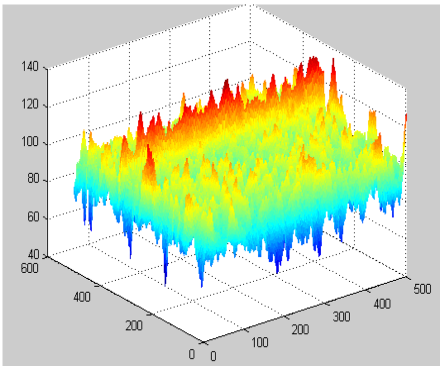
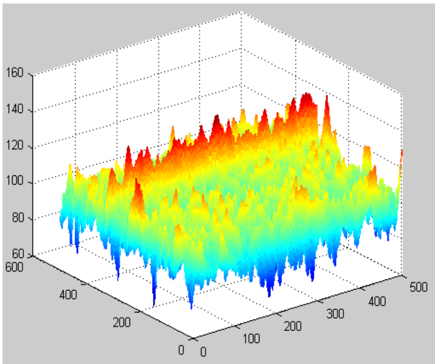
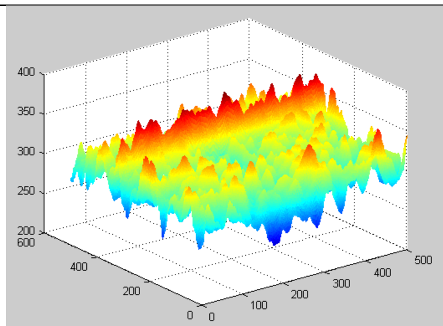
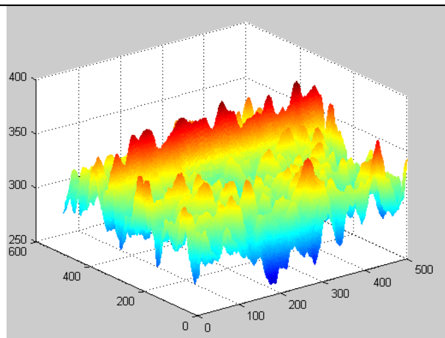
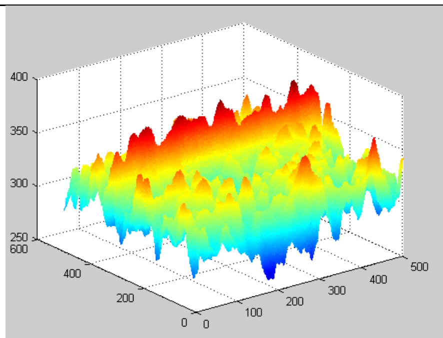
4	20	30	30, 60, 90,…, 360	
12	4	30	30, 60, 90,…, 360	
12	12	30	30, 60, 90,…, 360	
12	20	30	30, 60, 90,…, 360	

Figure 5.1 (Cont)

20	4	30	30, 60, 90,…, 360	
20	12	30	30, 60, 90,…, 360	
20	20	30	30, 60, 90,…, 360	

(b)

Figure 5.1(Cont)

In the designed FDDS system parameters are set as θ= [10, 20, 30, ... 360],size =30, and the standard deviations σ_x, σ_y=[2,4,6,…,28,30]. The parameters range can be increased to have better result at the expense of system processing time.

ii. Filtering

The proposed FDDS use two different DOOG filters to analyse the pattern properties, figure5.2 (b) and (c). DOOG outputs for these functions are given in figure 5.2(d) and (e). The combined DOOG outputs are given in figure5.2 (f). As seen two filter points the same defect and as a result the defect is emphasized.

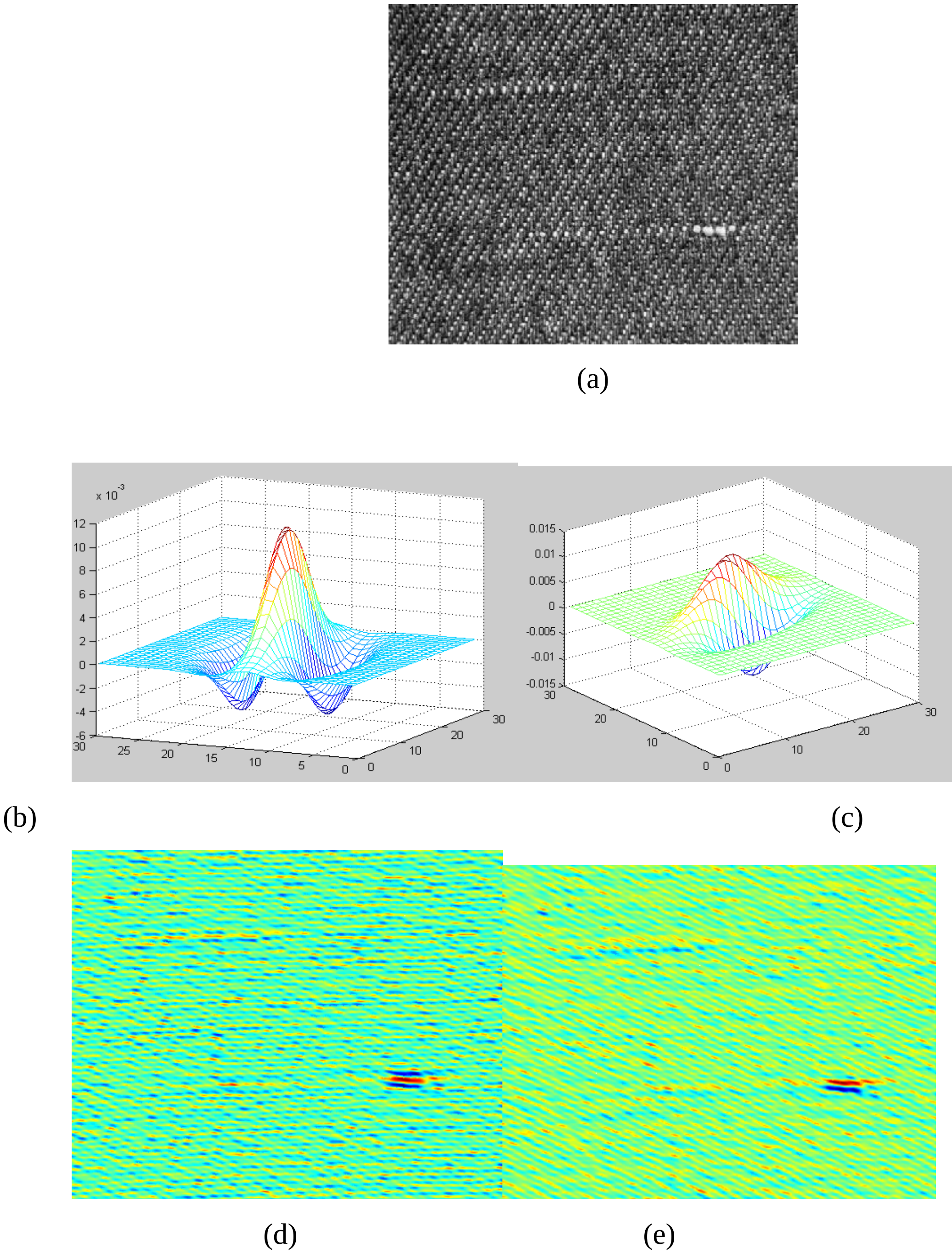
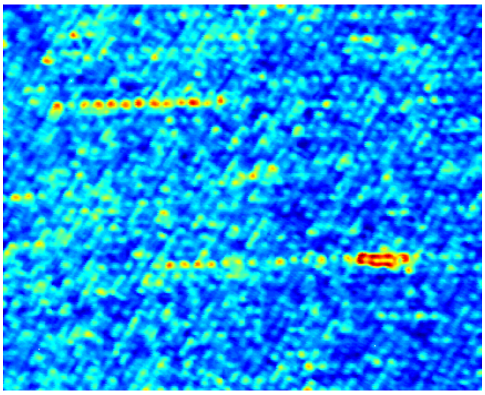


Fig 5.2 (a) The original image, (b) and (c) two DOOG filter. (d) and (e) The energy maps.



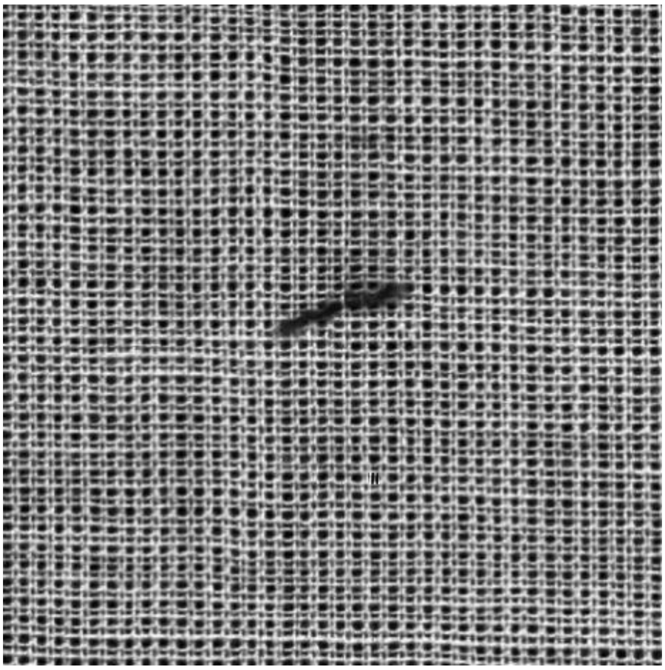
(f)

Fig 5.2 (Cont) (f) The combination of DOOG filter results.

The combined filter outputs show the energy magnitudes of patterns.The black shades show the low energy magnitudes, whereas white shades show the high energy magnitudes.

iii. Histogram process of Post processing

Following the calculation of DOOG filter outputs for various parameter sets there are a lot of filters and their results. In this case we must decide which filter is the best representative of the defects. Histogram analysing as described in section 4.4.3 finds the best matched filter output. Figure 5.3 shows the selected best filter its output and the corresponding histogram.



(a)

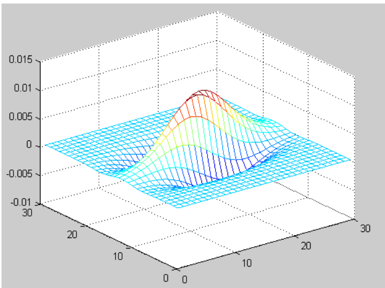
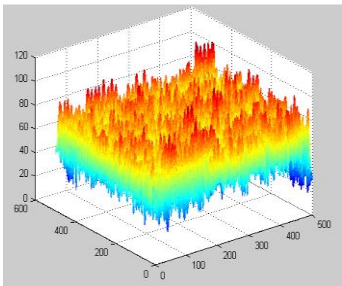
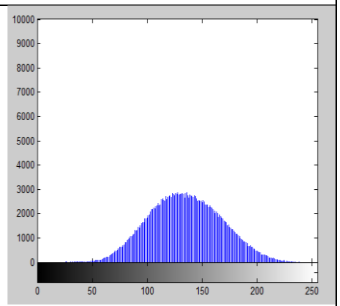
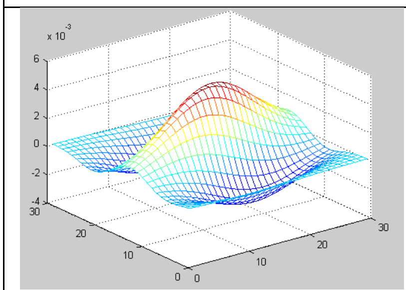
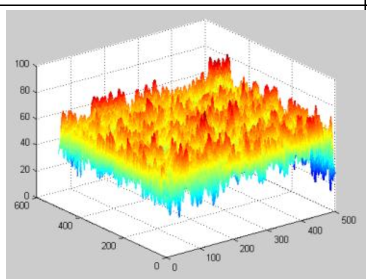
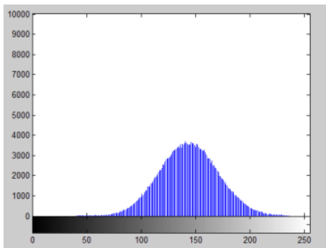
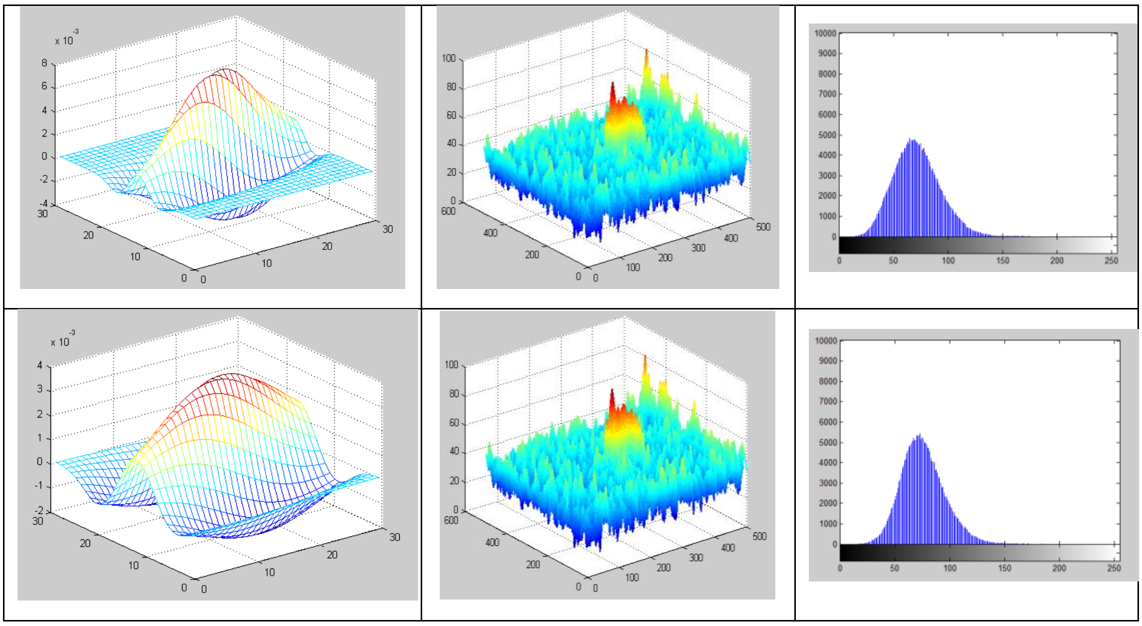
DOOG$_1$	Output of DOOG	Hist. of Output result
		
		

Figure 5.2 (a) An original image. (b) Various DOOG filter with different parameters, their results and the histograms.



(b)

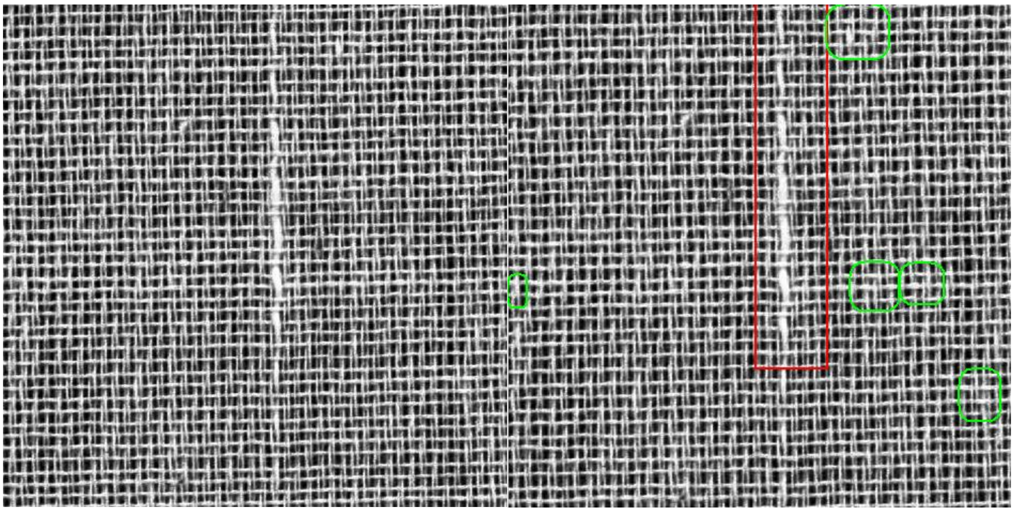
Figure 5.2 (Cont)

iv. Segmentation

After the best filter is obtained corresponding energy texture map is known.But the texture map does not show the exact information about defects. There are also some noises that affect the images and also the defect regions which must be separated from fabric pattern.Thresholding and morphologic applications are usedto obtain the defected regions. Moreover, a different DOOG filter is applied to the reduced size image to eliminate the noise parts from patterns. Then the defected areas in both of the images are compared to emphasize the actual defect. The figure 5.3 to 5.8 (a) shows the original image and figure 5.3-5.8 (b) shows the defects. The red colour gives the exact defect and green colour shows the possible defect to be further analysed.

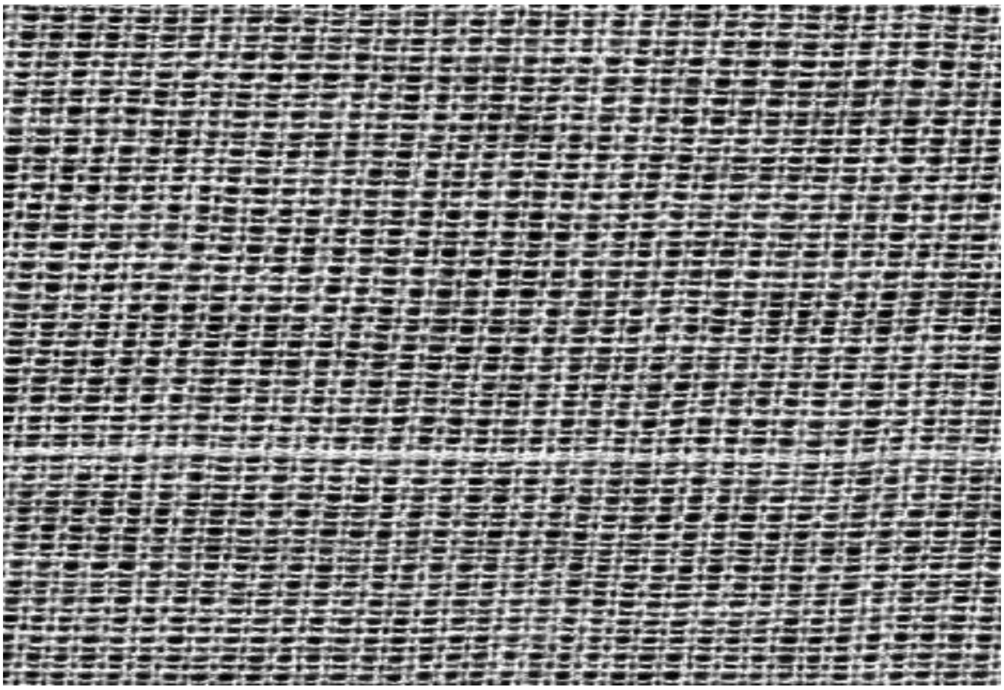
v. Classification

Classification process use GUI application that classifies the defects in 10 different groups.

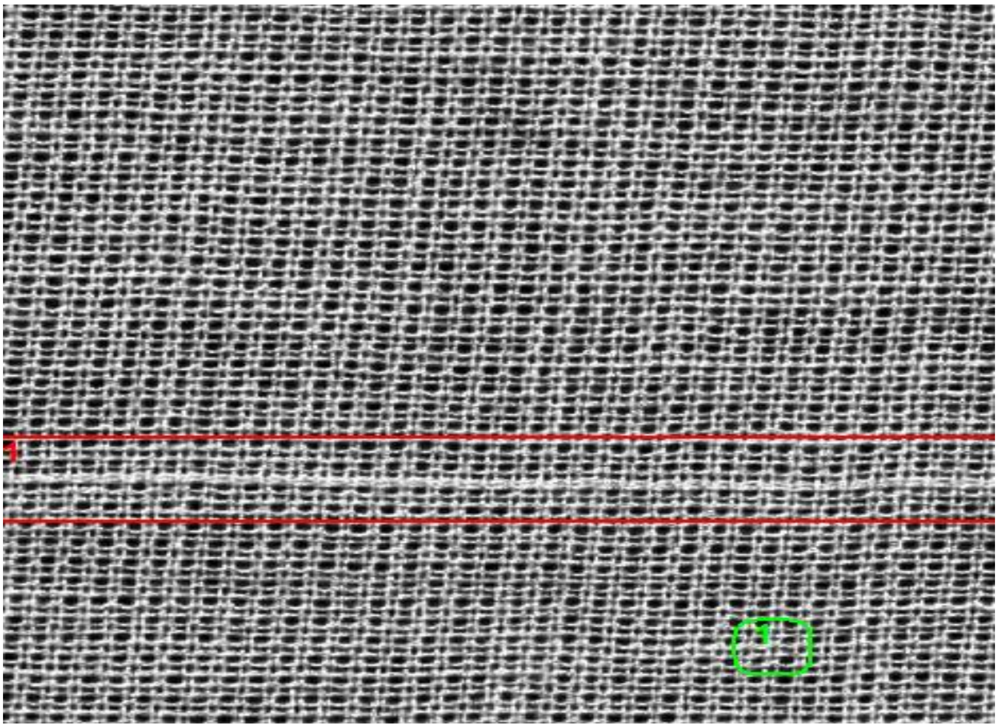


(a) (b)

Figure.5.3 Show the segmentation process (a) is the original image and (b) defect detected image that show exact and probable defects.



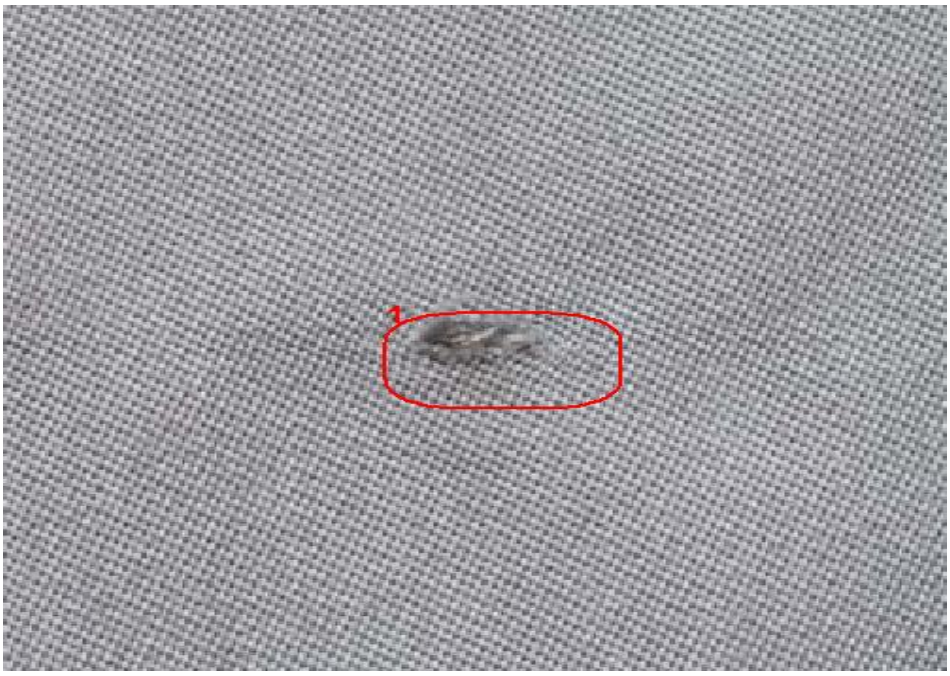
(a)



(b)

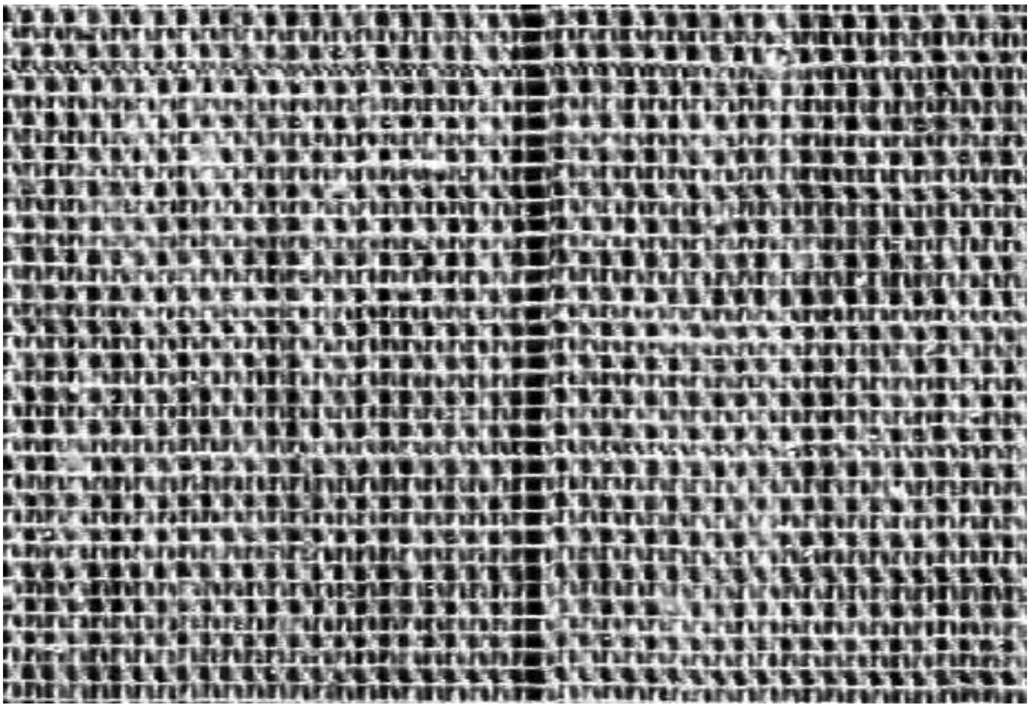
Figure.5.4 Show the segmentation process (a) is the original image and (b) defect detected image that show exact and probable defects.

(a)

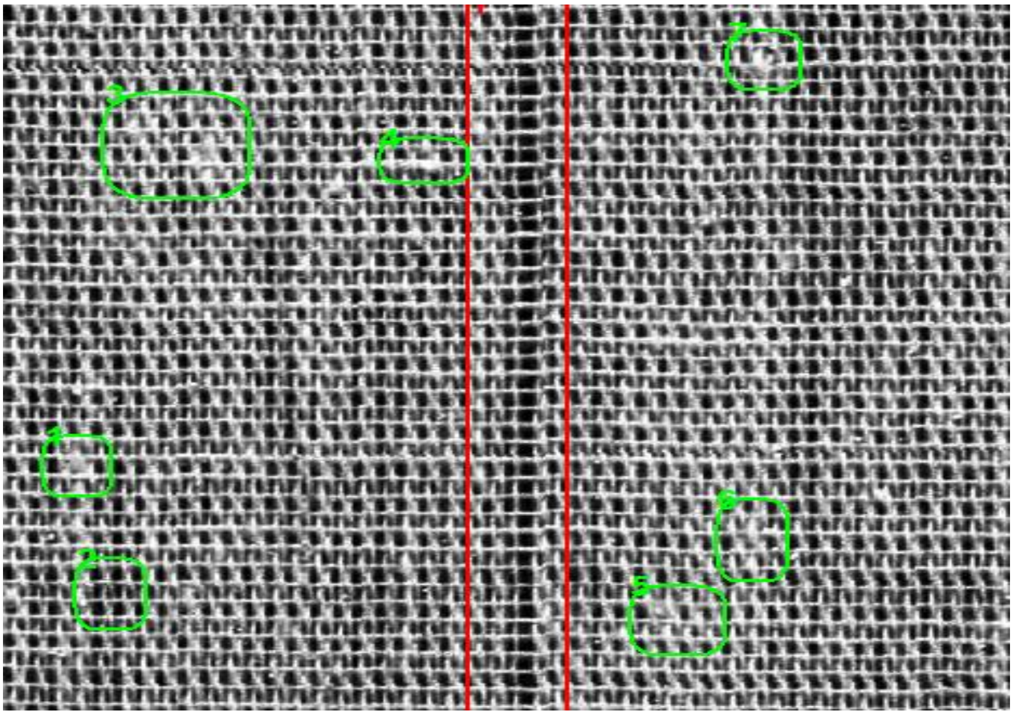


(b)

Figure.5.5 Show the segmentation process (a) is the original image and (b) defect detected image that show exact defects.

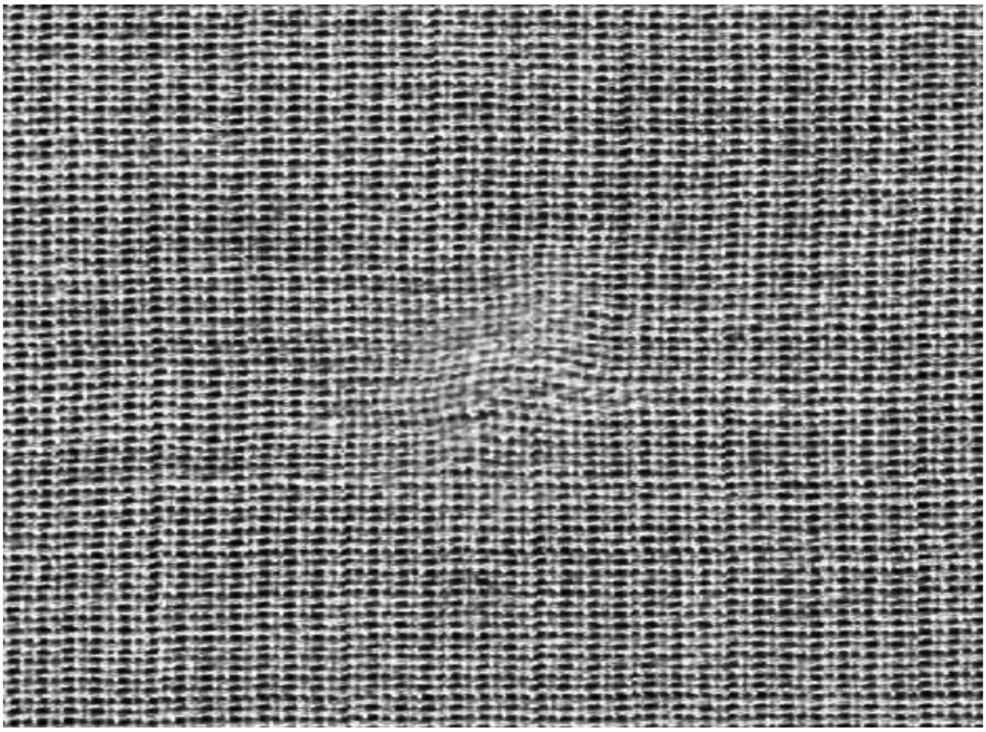


(a)

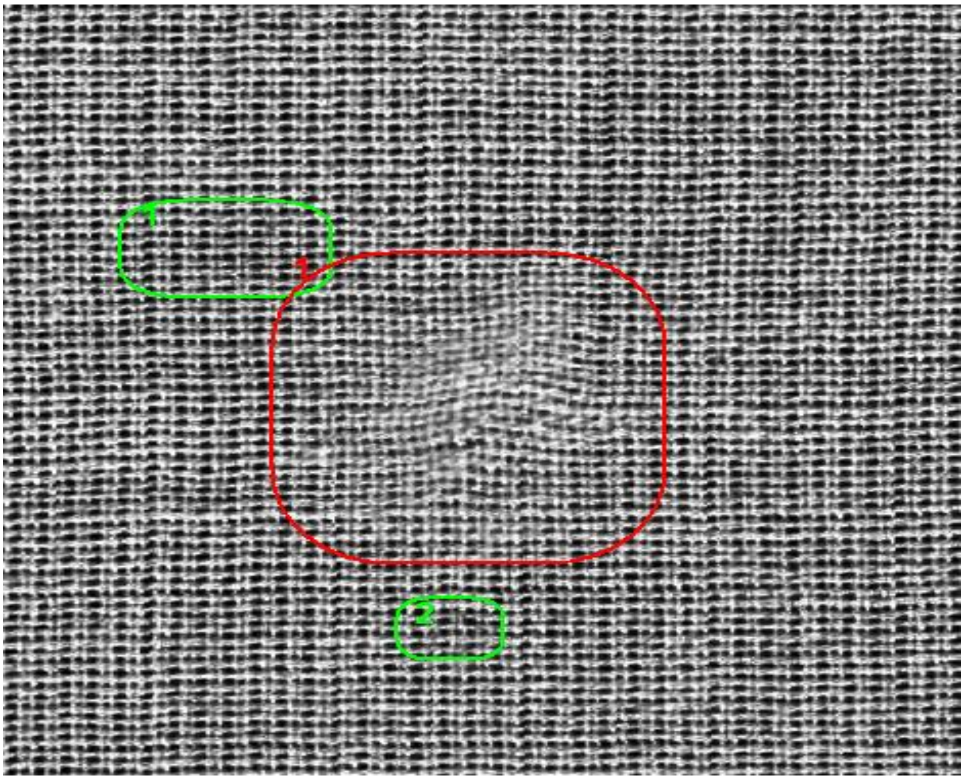


(b)

Figure.5.6 Show the segmentation process (a) is the original image and (b) defect detected image that show exact and probable defects.

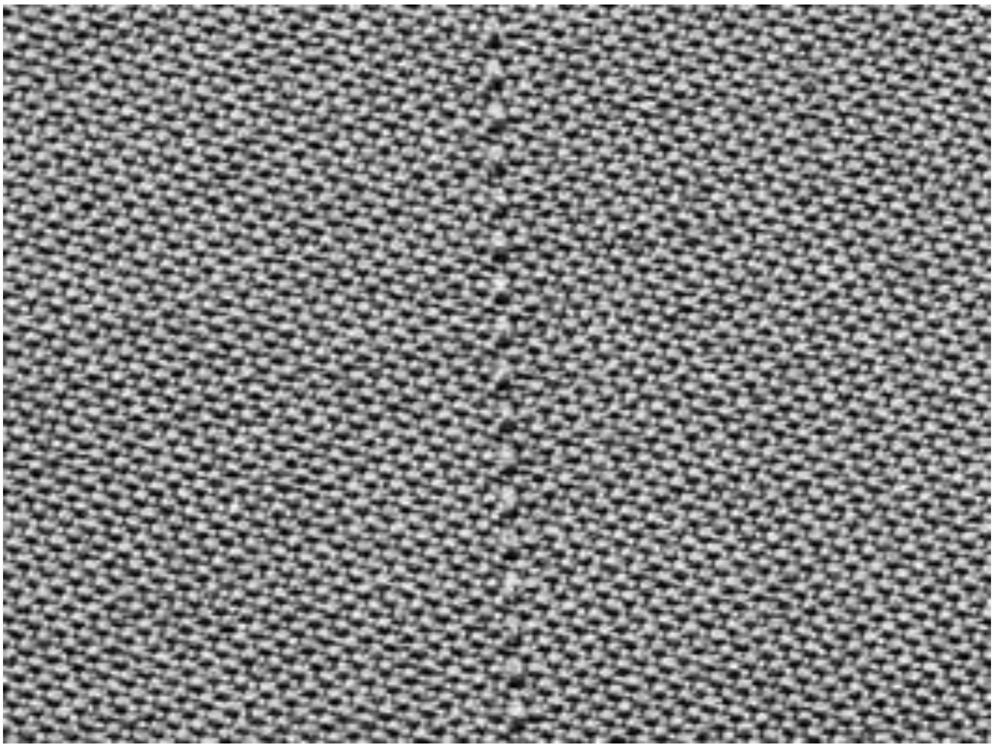


(a)

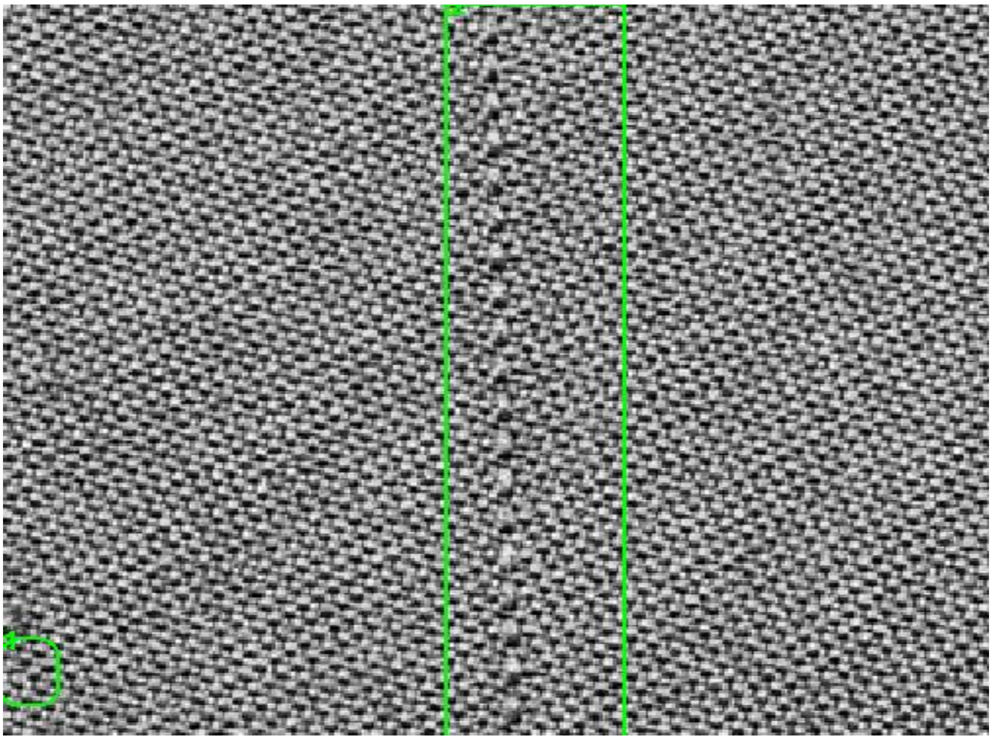


(b)

Figure.5.8 Show the segmentation process (a) is the original image and (b) defect detected image that show exact and probable defects.



(a)



(b)

Figure.5.9 Show the segmentation process (a) is the original image and (b) defect detected image that show probable defects.

5.2 Discussion of Results

In this study,a fabric defect detection system based on DOOG filters has been obtained proposed. In experimental work 32 different images with various types of defects were used. Some of the images are obtained from interned and some from real defected sample pattern. The designed FDDS is applied to all images and defects of out of these sample images have been recognized correctly. Only one image with 6 different defects was not fully satisfied. In this image 5 defects were correctly detected, but only one was missed.There might be various reasons for this missing. When this image is examined it was realized that lighting of the image is non-uniform. This defect was also very thin and small size. In general it can be said the proposed FDDS is very successful to identify defects.

CHAPTER SIX
CONCLUSIONS

6.1 Conclusions

Textile industry is growing with a large momentum and there are many obstacles to reduce the profit. The manufacturers also deal with quality issues to increase their profit rates. The manual inspections systems reduce the quality of fabrics because of the human' limited physiological nature. The interests to Fabric Defect Detection Systems (FDDS) are increasing day by day. Therefore, researches are forced to design high quality and faster fabric defect detection system.

The aim of our research is to design a high quality defect detection system. Fabrics are formed by thread groups that periodically woven. But, the easily affected structure of fabrics is the reason of distortions that occur on fabric patterns. The designed FDDS used Difference of offset Gaussian (DOOG) filter to implementing and detecting these distortions. DOOG filters are Gaussian based filters. They are obtained by differentiation of two Gaussian kernels with an offset distance. The reason to use the DOOG filter in this thesis is the clear definition of the structure and its simplicity. Moreover it was previously shown that it is good filter for texture analysis. Additionally, so far the filter has not been used for detecting defects in textile industry.

To increase the effectiveness of DOOG filter, many DOOG filters were generated with various standard deviations in x and y direction and filter rotation. This allows the implementation of different filters to fabrics, then a histogram analyser check which filter has the best result for segmentation. The multivariable parameters reduce the effects of defects with different shapes, dimension, and directions. In design and implementation stages, two DOOG filterswere designed as a complement of each other. Fabric patterns are complex and have changeable structure, so the features taken from two filters are better than one filter. In this research, the experimental study has proven that DOOG filters are right choice to detect the defected regions in fabric patterns.

The results of filters are shown as energy maps. The structure of filters, raise the energy magnitudes depending of the distortion on pattern. These energy maps give information about defects and their region. But there are several filters for each parameter set. The other part of the research is to use histogram analyser techniqueto define which filter is the best. Histograms give efficient features to compare the energy maps. The thresholds of defected regions are defined with histogram features. To emphasize the real defected part of the image, the image size is reduced and filtered with DOOG to compare with previous energy maps. The same defects in both energy maps show the strong defects, whereas the parts which is not exist in both energy maps may reflects the noisy or low energy defects. These parts can be reanalysed further.

The resolution and the illumination are very important factors in fabric inspection systems. The resolution of fabrics directly affects the result of fabric inspection system. It is relatively hard to get true features from low resolution and unclear fabric images. In such case the characteristic of the fabrics disappear, so it becomes difficult for the inspection systems to decide the defected regions. The illumination is another important factor, the abnormal illuminations on the fabrics may cause to extract misleading features,so the systems always detect the abnormal lighting area as a defect itself, even there is no defect. The resolution and illumination factors must always be kept in mind to design a high quality FDDS.

Classification is the last part of our research, detected defects can be classified into groups.This part was created to help the inspector to define the type of defects easily, so provide fast solutions in respect to source of defects. Finally in this thesis, a correctly working FDDShas been designed. In experimental work 32 different images with various types of defects were used. The designed FDDS is applied to all images and defects of 31 out of 32 sample images have been recognized correctly. Only one image with 6 different defects was not fully satisfied. In this image 5 defects were correctly detected, but only one was missed.There might be various reasons for this missing. When this image is examined it was realized that lighting of the image is non-uniform. This defect was also very thin and small size. In general it can be said the proposed FDDS is very successful to identify defects. If the success of the system is checked with more images, then the proposed system can be used to detect the defects as FDDS in textile industry.

6.2 Future Works

In designed fabric defect detection system the classification is only classify the defects by group. But as future work it is better to use a neural network or specific defect analyser to realize classification by defect types. Although with existing data set, the good system performance is obtained, it is better to increase the number of defected sample images.

It is also desirable to developing a full set of automatic fabric defect detection system including the proposed algorithms.

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