JULY 2015

M.Sc. in Textile Engineering

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UNIVERSITY OF GAZİANTEP

GRADUATE SCHOOL OF

NATURAL & APPLIED SCIENCES

NEPS DETECTION FOR WOOL FABRICS BY USING IMAGE PROCESSING TECHNIQUES

M. Sc. THESIS

IN

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BY

MURAT COŞKUN

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Neps Detection For Wool Fabrics By Using Image Processing Techniques

M.Sc. Thesis

in

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University of Gaziantep

Supervisor

Prof. Dr. Ali KİREÇCİ

by

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Murat COŞKUN

ABSTRACT

NEPS DETECTION FOR WOOL FABRICS BY USING IMAGE PROCESSING TECHNIQUES

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M.Sc. in Textile Engineering
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81 page

Image processing methods, started to be used for military targets in 1960s, have found usage opportunities in many areas thanks to advanced and fast computer technology. Textile is one of these areas. The process, made on the thesis includes efforts to identify neps on wool fabrics by means of on-line image processing using line scan cameras. Neps and foreign substance on fabric surface affect negatively quality of fabric. In the thesis image processing methods were analyzed and the most suitable method was determined for on line image processing of fabrics. Most of the image processing studies are related with the inspection and classification of fabric faults, however, this study aims on-line image processing to determine neps and their locations to be used for neps cleaning process by a robotic machine. As a consequence, the most suitable image process method was decided by systematically eliminating the others for neps type fabric faults. The selected method was practiced on a computer controlled neps cleaning robot for on line image processing and neps cleaning purpose. The process procedure starts with taking image of the fabric (1 meter length and 1.6 meters width) by means of two line scan cameras. The image then processed to determine faults (neps) and their locations. The location information is used as input data for robotic machine to achieve the coordinates of neps. Then, neps cleaning robot moves to the related coordinates and removes them in a systematic order. The scope of the thesis is limited with the analyzing the image processing methods and applications of the most suitable (fast and effective) method for the image processing.

Key Words: Image processing, fabric errors, neps

ÖZET

YÜNLÜ KUMAŞLARDA NEPS HATALARININ GÖRÜNTÜ İŞLEME TEKNİKLERİ İLE BELİRLENMESİ

COŞKUN, Murat
Yüksek Lisans Tezi, Tekstil Mühendisliği Bölümü
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Temmuz 2015
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1960'larda askeri amaçlarla kullanılmaya başlanan Görüntü İşleme metotları ileri ve hızlı bilgisayar teknolojisi sayesinde birçok alanda kullanım imkânları bulmuştur. Tekstil bunlardan birisidir. Bu tezde yapılan işlem, yünlü kumaşlar üzerinde bulunan nepsleri çizgi tarama kameraları yardımıyla online görüntü işleme metodunu kullanarak belirlemektedir. Kumaşın yüzeyindeki neps ve yabancı maddeler kumaşın kalitesini olumsuz etkiler. Tezde görüntü işleme metodları analiz edilmiştir ve kumaşların online görüntü işlemeleri için en uygun yöntem belirlenmiştir. Görüntü işleme çalışmalarının çoğunluğu, kumaş hatalarının incelemesi ve sınıflandırılması ile ilgilidir. Ancak bu çalışma bir robot makine ile nepsleri temizleme işlemi için kullanılarak nepsleri ve yerlerini belirlemek için online görüntü işlemini amaçlamaktadır. Sonuç olarak, en uygun görüntü işleme yöntemi, neps tipi hataları bulmak için kullanılan diğer metotları sistematik olarak elimine edilerek seçilmiştir. Seçilmiş yöntem bilgisayar kontrollü neps temizleyici bir robot üzerinde denenmiştir. İşlem prosedürü iki çizgi tarama kamera vasıtasıyla kumaşın görüntüsünü almakla başlar (1 m uzunluğunda ve 1,6 m genişliğinde). Daha sonra görüntü, elde edilen görüntü hatalarını (neps) görmek ve bu hataların yerlerini belirlemek için işlenir. Yerleşim bilgisi, robotik makine için giriş bilgileri olur ve nepslerin bulunduğu koordinatlar belirlenir. Bu aşamadan sonra neps temizleme robotu ilgili koordinatlara doğru hareket eder ve onları sistematik bir sırada çıkarır. Bu tezin kapsamı görüntü işleme metotlarını analiz etmek ve en uygun (hızlı ve etkili) metodu uygulamakla sınırlandırılmıştır.

Anahtar Kelimeler: Görüntü işleme, kumaş hataları, neps

To My Parents and My Fiancee…

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CONTENTS

LIST OF TABLES

Pages

LIST OF FIGURES

Pages

CHAPTER 1
INTRODUCTION

1.1 Introduction

Fabric manufacturing sector constitutes an important place with increased exports and capacity utilization rates in the terms of Turkish Textile Industry. In Turkey, there are a large number of small, medium, large scale fabric product facilities. Naturally, in the majorities of enterprises bring competitive conditions, also. Therefore, being defined errors to consist in the production stage enables to increase quality in a large rate and decrease these damage.

The image processing study is limited by determination of neps on the woolen fabrics in the scope of the thesis. For this purpose all the image processing methods are analyzed and the most suitable four methods are applied to determine the neps and their locations on the fabrics.

In the last 40 years, electronic data process has been progressed rapidly. This process has occurred the development in the computer process. Increase in memory capacity and data process speeds of computers have accelerated the development in the image processing technology. These developments have caused development of software used in numerical image processing technology.

1.2 Image process

1.2.1 What is the image processing?

Image processing is a computer study that is made in order to change properly measured or recorded electronic image data in electronic medium. Image processing is mostly used to process recorded available images; that is to change, estrange or make better available picture and graphics [1].

When it is came up in the view of image processing, human sensing system is known as the most complex system in the subject of image capture, grouping and analysis. Human vision system starts with our eyes. Many slotted wave size of light is percepted with the help of our eyes, each is a sensing system. Spectrum defines electromagnetic wave space to be seen by the human eyes. (Figure 1.1) in contrast, spectral space that a bee can see, starts in ultraviolet area and ends in green wave size [1].

Spectrum represents energy waves measured with length measurement unit and acting periodical. Wave sizes belonged to seen areas is 0.4µm-0.7µm [1].

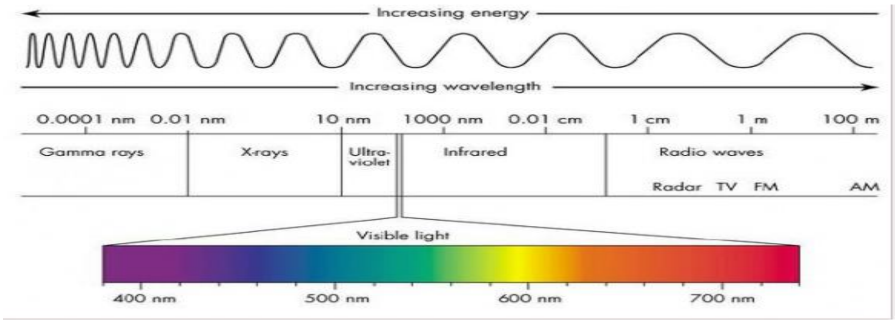

Figure 1.1 Electromagnetic wave space to be seen by the human eyes

We perceive electromagnetic waves in visibly areas and it is commented with our brain, we can transform image form. The main components of eye are cornea, pupil, lens, retina and optic nerves. Cornea, outside of eye, permeable and the form of dome has a function of focusing light. Pupil serves to turn on and off eye when light reaches to eye with the muscles, holding pupil. Pupil covers lens. With the aid of muscles, lens thickens or thins according to intensity of light, entering to eye.

It is necessary to make suitable data formats to computer medium so that pictures can be evaluated in computer medium. This transformation is called as digitizing. A photographic presentation of picture; more precisely; being transformed of picture to numerical form is possible with several methods. For this, scanners, numbered by picture can be given as an example by being used different techniques. Or by being used transformation of Analogue/Numerical,(Frame-Grabber) the systems that Picture is transformed to numerical; many slotted scanners placed to plane or satellite in remote sensing can be given as example.

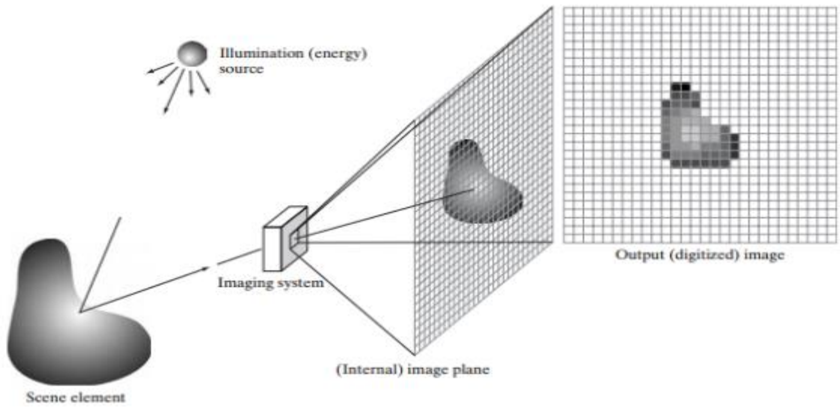

Figure 1.2 Perception and digitizing of image

Image process is a technology, providing that images taken digitally is processed and alteration and development of features and structure of images and with the aid of these images, analysis is made. Contemporary technology enables to be obtained data related to another image in wanted feature or image used as input by being used any image (photo or video) as input. With image process, the feature of image like colour, brightness, size, structure is to be changed, developed and analyzed by being used proper software. These software are used for many purpose such as being removed disorder of image transmitted to digital medium, taking a more quality image, define objects, decomposing active and inactive objects. Image process, providing to produce proper solution for every sector, being used images in different format can be used in countless areas like from security to astronomy; from defence industry to quality control.

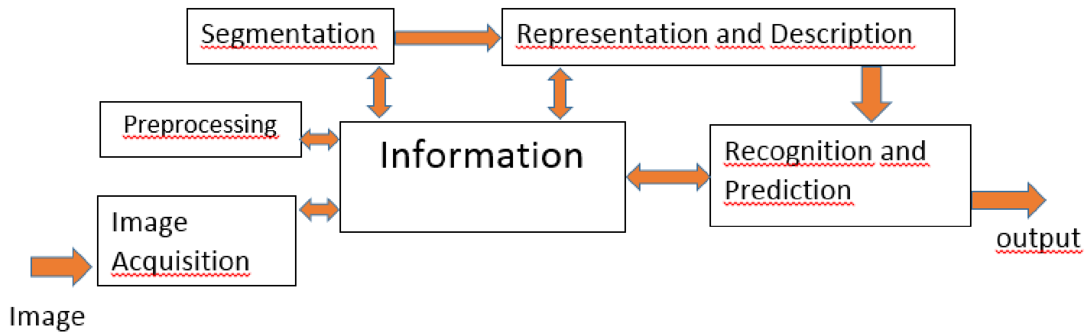

Figure 1.3 steps of image process

First step in image process is pixel receivers, providing that we take image from a film sheet from real world or a memory unit. In these apparatus, there are digitizer unit, rendering a pixel receiver and received pixel to numerical form. If pixel is not rendered to numerical directly, obtained analog pixel is rendered to numerical with the aid of an analog/numerical converter. The latter step from obtained numerical pixel is pre-processing. Pre-processing is that pixel is processed from pre-processing in order to obtain a more successful success before using obtained numerical pixel. For these process, we can give examples such as being arranged constant, being decreased and/ or disposed of images, separated the areas in pixel from each other. After pre-processing finishes, step of segmentation is passed. Segmentation is the process that is decomposed an object and background in a pixel or cared areas, having different features from each other. Segmentation is the most difficult application and results of segmentation can be a determined error rate. Segmentation produces raw information like borders, figure of image in a pixel or surface of object. If it cares about figures of objects, segmentation is waited to give information about edges, corners and borders of that object. But if it cares inner features like surface cover, surface, colours, skeleton of an object in pixel, regional segmentation is necessary to be used. Both of segmentation methods can be used together for solution rather complicated problems like pattern recognition characteristically or generally. The step after segmentation is to identification and demonstration of pixel. The last step of image process is to recognition and interpretation. Objects or areas are labelled properly according to predetermined definitions.

1.2.2 Image Types

Points, forming an image is called as pixel. Therefore a matrix forming (mxn) from m number on the horizontal and n number pixels in the vertical is thought. A pixel has two basic features:

1. Geometrical Feature: (x and y) matrix coordinates in image matrix.
2. Radiometric feature: gray value of pixel, perceived in electromagnetic spectrum.

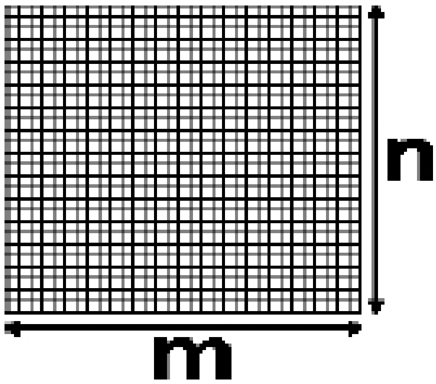

Figure 1.4 Image pixels

Black-White pixel is consider primarily in order to explain being numerical of a pixel. Black-White pixel is a pixel, having only two gray values. In such pixel, each pixel is thought as either black or white.

As an image grows, the possibility of detail comment in image approaches gradually to pixels. The basic difference between images in figures and binary image, expressed in Figure 1.5 is that each pixel value is different. However, pixels in binary image could take 0 or 1 value. In other words, they could be white or black. So, the reason of being different of gray values is that images compose from different gray tone values in images with gray tone. Gray value spaces are expressed as G= {0, 1, 2,..., 255}. The mean of this can be found 256 different gray tone value, more precisely gray value is found. 256 gray value is defined as one byte. 1 byte= 8 bit and it composes the inter-numbers 0-255 [1]. Principally, 0 gray value corresponds with black value; 255 gray value corresponds with white. Other gray tones compose in this values. Figure 1.7 show the images taken by gray values of 256, 128, 64, 32, 8 and 2. Note that figures become clearer as the value increases.

Figure 1.5 The grey colour values in various number

Another factor, affecting quality of image is pixel number in image. As the pixel number of image is increased, and because of change and increase of gray coloured numbers that equal to pixel in unit areas; pixelization in image starts in the form of square. The much more pixel number, because pixel number and colour number in unit area increase, quality and clearness of image increase. Therefore; it is important that pixel number is kept high in the view of a quality image process. Otherwise; details in image cannot be possible to be remarked.

1.2.3 Transformation of image to computer

In the view of study, the most important subject is the features of keeping picture by used camera; transformation of images to be analyzed to computer. At this point, it is necessary to take care about the subject related to working principles of photo machines and camera [2]. In photo machines, dropping how much light to photographic film is provided with mechanical cutter. While taking photograph, when shutter button is pressed, mechanical cutter opens and closes objective diaphragm during the pre-adjusted duration.

Figure 1.6 Open and close of diaphragm

Diaphragm pupil is opening and closing of snapshot of eyelid. The system adjusting duration of light dropping on film or sensor inside photo machine remarks the duration when is taken photograph. Snapshot is a curtain made from metal called sheet. Numerical values of snapshot are remarked as 1/8000, 1/4000, 1/1000, 1/500, 1/250, 1/125, 1/60, 1/30, 1/15, 1/8, 1/4, 1/2, 1, and 1’’, 2’’, 3’’. Time which light drops on film is called as exposure. It is made short exposure in Intense light; long exposure in weak light. Again; short exposure is called to stop activity, long exposure is called to make unsharp.

Taken photos with different cutter speeds from same angle and diaphragm width are given in Figure 1.7. a. Cutter duration of photo, given in figure 1.7.a is long (1 second), the activity is remarkable. Because Cutter duration of photo, given in figure 1.7.b is shorter (1/250 second), stretching in droplets is aforesaid. Because active image has been dropped on photo film in a shorter time. Duration of photo, given in figure 1.7.c is much shorter (1/2000 second), image has been nearly stopped and an instant image has been captured.

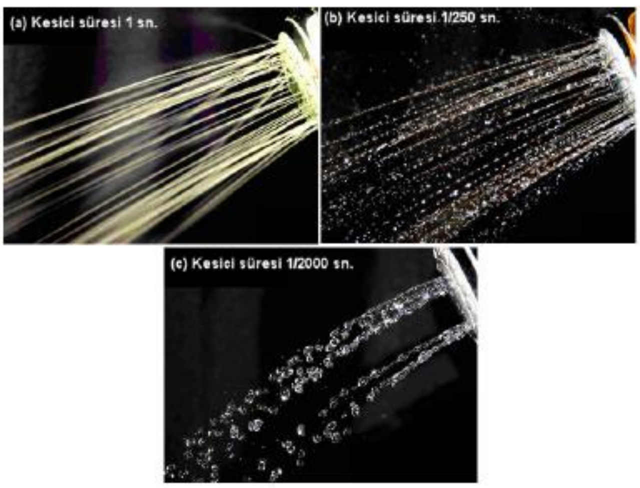

Figure 1.7 Images taken in different cutter time

Image in figure 1.7.a. reflects activity better; however camera needs to approach to high cutter speed and capture details in order to be examined yarn and fabric details in processes to be developed within thesis.

In video cameras, as different from photo machine, electronic cutters are used instead of mechanical cutter. Besides, instead of photo film in photo machine, image sensors are replaced. Image, dropping on sensor is initialized electronically. Therefore, a mechanical cutter is not needed. In order to perform function of mechanical cutter, sensor with a kind of switching system is be opened and closed in predetermined time.

1.2.4 Analysis and Determination of Activity

Entering usage of computer to nearly each point of human life has come together the necessity that outside world problems are perceived and solved. At this point, the subject of analysis of activity has been often a subject in computer world because of potential of using efficiently and productively in different areas like displacement, speed, sphere, depth, labelling, object pursuit and recognition.

In images, the subject of analysis of activity has been placed many applications such as military, biological, geographical, textile, agriculture research and comment of satellite with developed technology. Being used of the methods of analysis of activity in the solution of external medium problems like these derives a profit from time spent and materials. In this study, a software has been developed by being used MATLAB programming language in order to obtain various measurement results in fabrics.

1.3 Weaving

Weaving fabric is obtained by being tied in the form of large knit to be formed while two yarn series, forming from parallel yarns called as weft and warp are crossing each other in cross direction. As weft yarn twists to bobbin, with the help of a means of called shuttle, it is placed among warp yarns, formed a space, called as shedding among them by segregating to two series. In order to provide possibility for this process on weaving loom, warp yarns twist a cylinder, called as wrap loom, firstly parallel and tightly to each other. Warp yarns, twisting to wrap loom is put in order, preventing impairment of row in fabric of wrap wires and before each weft knitting of wrap yarns, the power providing to compose a shedding by segregating to two parts is reviewed by wires. The process made to prevent impairment of row of wrap yarns is called as lease; the process of power of review of wrap yarns is called as weaving draft. After weaving draft, wrap wires are made ready for weaving by being passed reed among backlashes.

1.3.1 Errors in weaving stage

Yarns, forming fabric is segregated as warp and weft yarns. Errors, made in spinning factory during manufacture of these yarns, reflect to fabric exactly and errors of fabric come out in case yarn is not exposed to a good clearance. Except of these, in weaving preparation stage, many errors made carelessly or intentionally are included to error class to warp in fabric or weft. Errors, stemming from machine or labour in weaving process come out in the form of important errors as fabric plane or surface. Errors, seen in fabric is classified as thin warp-thin weft error; thick warp-thick weft error; fish-nep-flame errors; complicated warp-complicated weft error; error of disconnected of warp (disorder of warp); error of disorder of weft, double weft error and adrift weft error. Thesis study includes neps error inside these errors.

1.3.2 What is neps?

Neps is fiber nodule, seen in the form of size of pin head or less smaller and black points. It is an error seen in both warp and weft yarns. Mass of yarn (black points), forming because of yarn, curved in the stage of spinning of yarn is called as neps. In the process of cleaning of neps, because of increase disengagement of yarn, neps does not generally be cleaned in the stage of bobbin. They are seen as small white points on the surface of fabric. In case neps are not cleaned in yarn machine, fabric can take to direction of warp or weft.

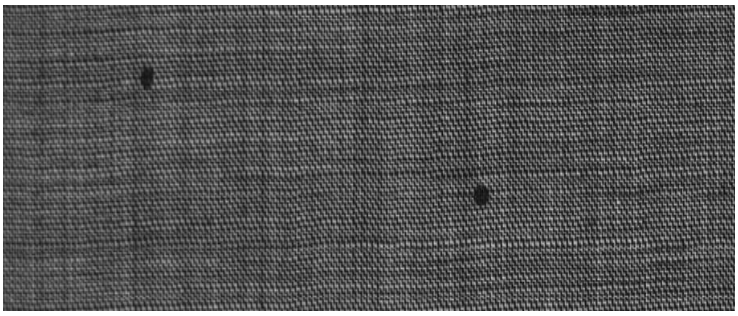

Figure 1.8 Neps error in weaved fabric

When a group from single fiber or fibers is kept loosely between two surfaces, one cylinder or two cylinders, turning in the same or different direction; one is static and the other passes through active, because of friction, coming out between two surfaces with fibres, a ripple (nodule) is formed by twisting of fiber. To prevent this type neps, distances among elements of machine are adjusted and consequently fiber is under control. Second reason that neps cause is disengagement of fiber in the stage of the process. Because fibres extend, they will have elastic energy. When a fiber comes off, tension is suddenly free, it covers ends of disengagement and henceforth neps starts to form. To prevent this type neps, speed of parts of machine is adjusted.

1.4 Introduction of error diverge

Especially, in wool fabrics, processes purity of errors, coming out on the surface of fabric cause intense labour and cost. Besides, for these processes, it can occur problems about finding qualified personnel. Neps are errors that occur intensely beside of fabric error in various type (like double weft, warp disengagement, loose weft, tense weft, run of weft, loosely woven sparse weft and nodule) (approximately 30 neps/m^2). By depending on error type, being removed each error can change between a couple of seconds and hours. Available neps and other errors are be cleaned manually by workers in fabric control tables of the depart called as nipper-home of operation. To be removed errors, a fabric passes thirdly as raw fabric, semi-finished fabric and finished fabric from fabric control tables. This process causes a nonstandard of production beside of important labour expense.

In this study, a part of fabric surface is scanned by cameras and image, obtained the result of scanning is analysed with a software to be developed as part of study and only coordinates of areas, neps will be remarked.

Nowadays, extreme increase in speeds of production and fertility of textile machines have been seen. Increased production capacity causes some problems like overlooked errors in the parts of quality control or employ much more workers to control all fabrics. So, it is important that a manufacturer can measure quality during production in order to increase the fertility of production by producing less poor quality production and decreasing costs related to quality control [3]

In quality control departs of most of textile operations, control of fabric is performed by humans [4, 5]. In this case, the possibility of overlooking an error in or on the surface of fabric by the people, controlling fabric is high and it is impossible that people can see all of quality control table in given time because of size of fabric. Made studies present that visage control capacity of human has capacity that it will approximately determine 60%- 75% of clear errors in fabric [6].

1.5 Previous Studies

Quality control of fabric is a rather important matter in textile industry. With the help of eye subjectively; in quality control of a fabric, having width between 1.60-2.0 m and progressing approximate with 10 m speed in minute, it is difficult that various weaving or knitting errors are remarked. So, it is available many studies that fabric quality control is made with the help of computer (machine vision). Some of studies, made of the purpose of determination of fabric errors are given here in below.

In the study, made by Mak K. L., Peng P. and Yiu K.F.C. [7] determination schema of a new error, making error determination automatically for weaved fabric and depending on morphological filtration is developed. In developed method, error of fabric is tried to determine by being used Gabor ripple net. Because developed determination schema of error require morphological filtration, quantity of related calculation charge is less than other methods. The performance of developed system on different frequency and featured fabric and results of test prove efficiency of demonstrated perception arrangement.

In this study, made by Stojanovicw R., Mitropulos P., Koulamas C., Karayiannis Y, Koubias S. and Papadopoulos G. [8] they made quality control of fabric with a vision based system. They composed a developed general equipment and software platform and prepared a strong algorithm. While system is making determination of error, being of its correction is high, rate of giving false alarm is low, harmony with Standard control devices and low cost is the basic advantages of system in view of other error determination system.

In this study, made by Abouelela A., Hazem M.A, Eldeeb H., Abdelmonem A.W. and Nassar S.M. [9] they studied on system of automatic vision error determination, presented a detailed system configuration and proposed an algorithm of error determination. They supported that industrial artificial vision systems have to run as real time, it has to be flexible to produce rate of low false alarm and meet transformation of control areas and included simple statistical features (mean, variation, median). The results have shown that this system will determine various featured changeable errors as dimension and structural with the rate of too low false perception.

Chan C. and Pang K.H. [5] used a type of fabric in order to understand the relation between image gap, frequency zone and composition of the fabric.3D frequency spectrum, two important spectrum analysis were used to detect fabric fault. This system divides the faults into four categories: double fiber, lack of fiber, broken fiber and the difference of fiber intensity. After evaluating these four categories some of types and actual samples were selected for a frequency spectrum and seven characteristic parameters of fault classification.

Dorrity J.L. , Vachtsevanos G., Warren J. [10] had a work on detection of fabric fault and control on weaving period and apparatus were designed to model actual loom conditions. The image detection with CCD camera periodical analysis were used. As a light to transmit to fabric, fluorescent was used. With the help of images, fault detection were gained by using way of taking wavelet. The parameters of wavelet analysis were divided into three categories as high, middle and low. According to the tests, the most common fabric faults were determined.

Meylani and his friends [11, 12] used the cage filtration in order to control quality control of fabric surface. At this work, three, six and eight parameters, two dimensional gradient based adjustment, cage filter were determined as a method of fault detection. A technique of histogram changing was used for the prior processing of fabric image, and it was understood that to detect the faults is possible with the help of a suggested diagram.

According to work by Serdaroğlu A., Ertüzün A., Erçil A. [13] a new technique was developed by combining the wavelet transformation and ICA (Independent Component Analysis) for default detection and was tried on real fabrics. It was observed that Before ICA, the rate of fault detection was very high compared to one by one usage of the techniques.

Henry Y.T.N. [14] made a work on fabric fault detection by using wavelet based techniques and as a result, it was stated that WGIS (wavelet pre-processed golden image subtraction) was the best technique for fabric fault detection.

Kumar A. [15] divided the techniques of fabric fault detection as: based techniques and made tests by using these three techniques. Statistical, spectral and model based techniques had a diversity in terms of gained results. It was understood that the combination of these techniques had a better results than one by one usage of these techniques. This combination technique is suggested for researches in the future.

Mursalin E. T., Eishita F. Z., Islam A. R. [16] made a work by using the methods of nerve net and micro controller. At this work, it was understood that hole default measurement accuracy on fabric is %86, abrage detection accuracy is %66, stripe fault detection accuracy is %77. The general average of fault detection was measured as %76.

Yanfang Han, Pengfei Shi have investigated detecting fabric fault by using wavelet method. At this work, it was certainly observed that when it is compared to the traditional frequency filtration techniques (butterworth, expon, lower trapezium and high filtration), wavelet model had a better result. But at this work they focused on images of high frequency fabrics, and they stated that Further experiments and much more works were needed for other fabric patterns.

Mahajan P.M., Kolhe S.R. and Patil A. [18] made a research on automatic fabric fault detection techniques. They observed all the techniques in a detailed way. They divided their works as statistical, spectral and model based techniques.

Thilepa R. [19] MATLAB made a research on image processing technique and automatic fault detection and used the Matlab7.3 version of Textile Fault Detection System. He observed that this version had the ability of detecting the fabric faults at the high level of accuracy and performance and the density of histogram and sill images.

Nasira G. M., Banumathi P. [20] made a research on fault detecting on fabric by using a new smart and automatic fault detecting model. This model gains the digital fabric images with the help of diagnostic image device and it transforms the images into dual images by using restoration and threshold techniques .Processed image output was used for input for the neural network(a back-spread algorism).The nominal factors were calculated and the automatic classification of faults was made.

Escofet J., Navarro R., Millan S.M. [21] stated that Image analysis technique is used for detecting local faults on textile material. At this work, in order to develop the system which is controlled subjectively, a full automatic computer based, efficient and reliable industrial application was made. At this system, the version was copied by using Gabor wavelet nets. The most important advantage of this system is that it has no need to any adjustment. Only the optical conditions (Brightness and scaling) should be taken granted. This system was tried on different shapes, composition and size of the fault and the efficiency of system was proved. Apart from being applied to different textile materials, it can detect the variety of the faults.

According to Elragal M. H. [22] the aim of this work is to develop automatic detecting system instead of using visual controlling made by human being. The purpose of this work is high accuracy of fabric fault detection and classification of fabric faults. In order to detect fault and classify them, this system consist of a computer based visual system for capturing images and an image process device for adjusting images and features of the faults. The first one is flu condensation system (FCM) and the other one is adaptive neural flu inference system (ANFIS).According to experimental results, suggested systems have the capability of detecting the faults and classifying them. According to experimental results ANFIS has a better result than FCM in term of classifying accuracy of the faults.

In his study, Çelik H.İ. [23] aimed to develop an algorithm to classify and determine error of fiber automatically and plan prototypical artificial vision system for fiber super vision machines. Three different error supervision algorithms were used; Linear filtering (LF), Gabor filter (GF) and Wavelet analysis (WA). These algorithms were applied as five different type of error: as real time and out of real time over warp lacking, weft lacking, hole, oil spot, and knot. In the end, the rate of algorithm classification was statistically evaluated. The classification of the faults have been made by using Artificial Intelligence (AI) techniques. The classification of faults have been achieved with 97% accuracy.

When the recent works are examined, most of the studies are related with computer based systems which have been tried and improved in the field of fault detection and classification of faults. A study related with on line automatic fault detection and cleaning is not encountered in the literature survey.

CHAPTER 2

MATERIAL AND METHOD

2.1. Fabric Detection

Product detection is most important in manufacturing industries such as automotive, medical, electronics and textile industries. Chiefly, fabric fault inspection has two type possibilities [15]. The first is the product detection (off-line) in that manufactured fabric has to be detected through fabric detection machines [24, 25]. The second is the process (on-line) in that the weaving process can be controlled for appearance of faults.

2.1.1. Traditional Fabric Detection

Typical fabric web is 1,5-2 meters wide. In addition, detection of faults are numerous and complex appearance [26]. Accordingly, fabric web detection has outstanding high requirements and is most attracting compared to the other detection problems. Texture web may have same faults such as homogeneity, coarseness, unevenness and the variety of its faults [27, 28]. Traditionally, this process must controlled by human detectors [29, 30, 31]. Most mills have power driven detection machines where manufactured fabric roll is removed from weaving machines and unrolled on the detection table at speed of 8 - 20 m/min. When the detector notices a fault on the moving fabric web, the detector stops the machine, notes the faults and starts the machine again. For each detected fabric web, the faults number parameter length is computed and the fabric is categorized [15, 29, 3, 32, 33].

Drawbacks of traditional fabric detection;

- Human requires training and their abilities take time to improve.
- Visual detection is tiresome and difficult.
- Human control is slower and a time consuming task.
- Human inspectors get tired after long time.

- The controller make mistakes because detection is trustless when the width of fabric 1,5–2 meters at a speed of 20 m/min.

The inspectors can hardly determine the level of defects is acceptable.

- This process is slow and diversity from mill to mill.
- Quality control speed is low when compared to the production speed.
- It is highly difficult to success 100 % fabric detection with the traditional process.
- This traditional fabric detection is costly.

2.1.2 Automated Fabric Detection

Automatic detection systems are designed to increase the accuracy, conformity and speed in fabric manufacturing process to decrease cost, improve the quality and develop efficiency. [34]. The main common alternative to human visual fault inspection is the use of a computer vision system to inspect differences between images procured by a camera.Industrial web materials like fabrics take many forms however there is a spectacular similarity in visual detection method can be broken down into a sequence of processing stages; image achievement, speciality extraction, comparison and decision.

2.1.3 Online Automated Fabric Detection

The main scope of this vision method is to inspect the faults at an early production stage so that to inhibit foreseeable fabric faults in mass production.

- The system must managein real-time with very good results,
- It must decrease escape rates
- It must decrease false alarms,
- It must be durable and flexible.
- It must be speedy and low cost,
- The system must be easily to apply and maintain.

Consequently, an influential online automated detection is a key factor for the increase of competitiveness of the textile industry [24, 25]. This system advantages are;

- The results of this system are creditable and quotable.
- The system can increase the influential of production and enhance product quality.
- A good system means that lower cost.
- The system has shorter production time.

2.2. Fabric Defects

Textile defects or blemishes have the effect about 85% of the blemishes obtainedin the clothing industry [35]. It is considerable thus to determine, to define and to prohibit these blemishes from reoccurring. The fabric quality is influenced by yarn quality and/or loom blemishes. The low quality raw materials and in adaptable conditioning of yarn results in yarn quality faults and influences such as color, hairiness, slubs, broken ends, etc.

Figure 2.1 shown that, the automation problems are categorized in two different types depends on the kinds of web materials.[36]

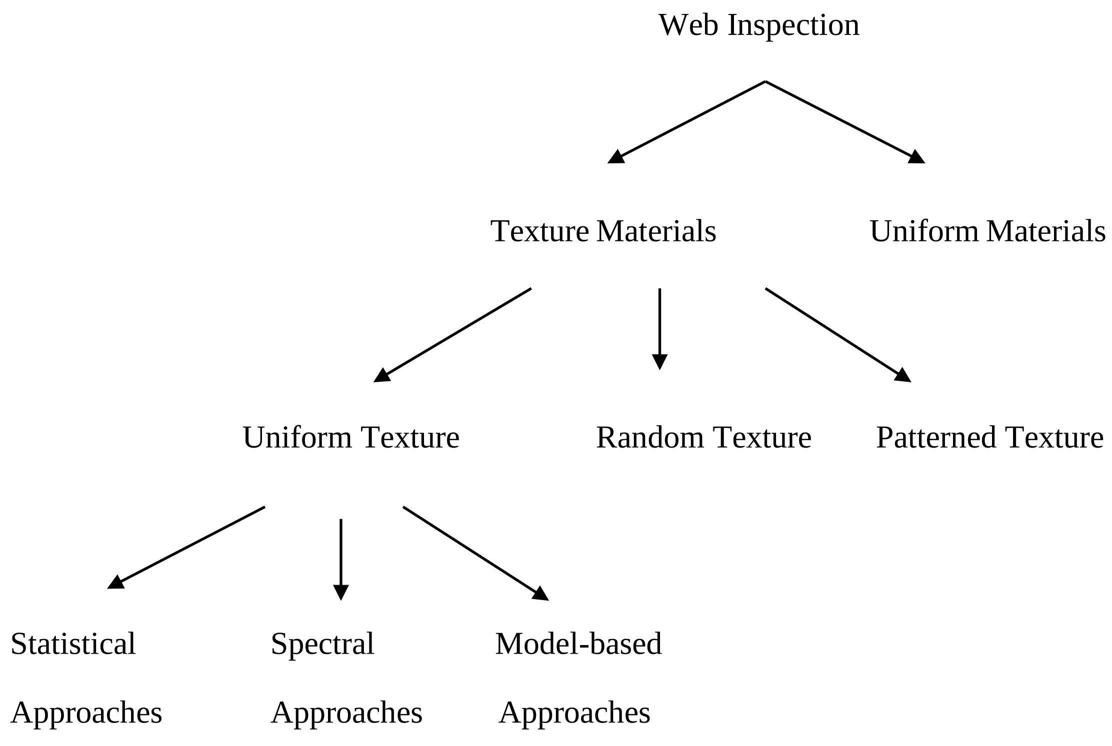

Figure 2.1. Classification of a web inspection problem based on the nature of the surface

The first category will be correlated with uniform web materials such as papers, films, metals, and so on. Fault determination within theseweb materials usually is based upon identification of areas that differ from a uniform back-ground. The other category of web control problems are associated with textured materials for example textile, ceramics, plastics, and so on. The feature of blemishes within textured materials is often not clearly described. For that reason, the visual supervision in textured materials consists of gradingthe materials depend on the all round texture characteristics such as material isotropy, homogeneity, and texture roughness. The textured materials can be divided into uniform, random, or patterned textures [37].

Brazakovic et al. [38] have informed a model-based method for the supervision of random textured materials. The issue of printed textures (e.g. printed fabrics, printed currency, and wallpaper) needs the assessment of color uniformity and compatibility of printed patterns.

2.3. Description of Methods

Nowadays; several programs have been investigated with suitable methods. Usage of the methods belonged to the image processing toolbox of Matlab programming language has been proposed in order to determine error of neps on the fabric classification belonged to the methods has been given in the Figure2.2.

Table 2.1 Defect Detection Methods

Approaches	
Statistical Approaches	1.Matrix Method
	2.Local Linear Transforms
	3.Fractal dimension
	4.Edge Detection
	5.Cross-correlation
	6.Gray-Level Statistics
	7.Bi-Level Thresholding
	8.Morphological Operation
	9.Neural Networks
	10.Fuzzy Logic Method
	11.Eigenfilters
	12.Histogram Method
Spectral Approaches	1.Fourier Transform
	2.Gabor Filter
	3.Optimized Fir Filters
	4.Wigner Distributions
	5.Wavelet Transform
Model-Based Approaches	1.Gauss Markov Model
	2.Poissonian Model
	3.Model-Based Clustering

2.3.1 Statistical Approaches

Statistical texture analysis methods measure the spatial distribution of pixel values. An essential assumption on this technique is that the statistics of defects free regions are stationary, and these regions extend over the considerable area of inspection graphics.

Statistical procedures can be grouped in to first- order(one pixel), second-order (two pixels) and higher- order(three or maybe more pixels) studies depending on quite a few pixels identifying the regional capabilities. The first -order studies estimate components such as the average and variance of specific pixel valuations, ignoring the spatial interplay image pixels, second and larger order studies in spite of estimate features of two or more pixel valuations occurring at particular location relative to each other. The fault determination methods are matrix features, local linear transforms, fractal dimension, edge detection, cross-correlation, gray-level statistics, bi-level thresholding, morphological operations, neural networks, fuzzy logic,eigenfilters and histogram have been classified into that class [39].

2.3.1.1 Defect Detection Using Matrix Method

The matrix process, recognized furthermore as the spatial gray-level dependence procedure, has been widespread used in texture analysis. It is depend on repeated occurrences of different grey level configurations in a texture. Automatic visual inspection approaches for textured images usually calculate a set of textural properties on the spatial domain or on the spectral domain. The co-occurrence matrix is one of the most widely used statistical structure analysis tools for fabric fault inspection [41].

In spite of it is popular and lots of research referred this as highly accurate technique, the co-occurrence matrix characteristic has a lot of disadvantages. It is long time while there is no generally recognized remedy for optimising the displacement vector. Besides, the amount of gray levels is generally decreased in order to keep the size of the co-occurrence matrix controllable. Furthermore, this method is usually computationally costly for the demands of a real time fault inspection method [15, 25, 27, 41].

There are two major issues inside traditional use of the co-occurrence matrix with fabric fault inspection (influential dividing of co-occurrence space and influential explanation of Multiple pixel co-occurrence), that should be referred to success greatest functionality for on-line fabric detection. Furthermore, the asymmetric co-occurrence matrix consists of more details about structure orientation and therefore need to be preferred than the symmetric ones [15].

Tsai *et al.* [42] have examined a method of detecting fabric defects that have been classified different categories by a neural network and fabric defect detection in using only two features, i.e. contrast and degree (direction) achieved a classification rate as high as 96%.The two of these observations have encouraged the researchers to consider removing co-occurrence characteristics from sub-band images. Benefit of this kind of approach will be two drape: Primary, dealing with smaller images would mean enhancement in the computational performance considering that the computational complexity of co-occurrence matrices will increase while the size of the image will increase. Next, disregarding greater rate of recurrence bands that quite often use a noise-like appearance and emphasizing the lower resolution images may improve the faults in accordance with the back-ground texture. Hence, utilizing sub-band domain characteristics (as it is known as here) have increased the fault inspection rates when compared to the characteristics produced from SDCM.The suggested fault inspection method has two stages [43]: (i) The characteristic removal aspect first uses WT to segment textured images into sub-bands and then components co-occurrence characteristics from the sub-bands in addition to (ii) the inspection aspect, the Mahalanobis-distance classifier that is instructed by means of defect-free samples.

2.3.1.2 Defect Detection Using Local Linear Transforms

Texture properties can be extracted by using several bi dimensional transform such as Discrete Cosine Transform (DCT), Discrete Sine Transform (DST), Discrete Hadamard Transform (DHT), Karhunen –Loeve Transform (KLT) and eigen filtering.

In online fabric defect detection, the local transforms for instance DCT or DST may be prefer capable of the eigen filters or KL transforms, since DCT or DST is usually directly obtained from the camera hardware using in a commercial sense available chips in which perform fast and effective DCT or DST transforms.

The important information in most fabric textures can be contained in greater order relationships among image pixels [34].

Unser [44] has investigated different local linear transforms for texture classification and found KLT as the best algorithm.

Also Ade et al. [45] have compared laws filters, KLT, DCT and DHT for textile defect detection. In experiment results investigated, the KLT performance, particularly on larger window size, was amongst the best.

2.3.1.3 Defect Detection Using Fractal Dimension

Fractal-based texture analysis was introduced by Pentland [46]. According to study of [39] box counting as the process of estimating the probability that m points lie in the box. In fact this method has computationally sufficient to be suited to PC implementation, however provides very restricted experimental results which suggest 96% inspection on eight types of faults. The localization accuracy of these inspected faults are very weak and high false alarm.According to of methods for fractal dimension (FD) assessment, a few disadvantages have been found. In many cases, this method does not cover all probable (FD) ranges for textiles, that may be, any value from 2. 0 to 3. 0, therefore it is not suitable to various kinds of textiles. Moreover, the technique has a weak efficiency and high false alarms rate [15, 25, 27, 47].

Keller et al. [48] suggested an adjustment of process owing toVoss, that presents acceptable results up to FD = 2.75.The usage of fractal dimension is investigated by Conci and Proenca [49] for discriminating faulty areas. The decision for blemish report is depend on the variation of FD.

2.3.1.4 Defect Detection Using Edge Detection

Edges may be determined as micro edges utilizing little edge operator masks or while macro edges utilizing extensive masks [50]. The particular distribution of level of edges per unit region is a critical characteristic in the textured pictures. The quantity of gray level transitions in the fabric image can easily signifies range, edges, points, ripples along with spatial discontinuities. These characteristics are already utilized to detect fabric faults [51, 52, 53]. These approaches are proper for plain weave fabrics imaged at low resolution. Although the difficulty within separating fabric faults with the using the noise generated from the fabric structure results in high false alarm rate and so that makes them much less charming for textile detection.

Conci and Proença [26, 47] have presented a simple system designed for fabric detection and the results shown that the success of system implementation based on the choice of the specific approach. They have applied three techniques and compared their ability to detect faults. All methods (fractal dimension, edge detection, or threshold) shown accuracies greater than 85% on average. But, the degree of accuracy based on the fault type. The fractal dimension method in faulty textile image identification achieves an overall 100% (only 2% false fail alarms on average) and is faster than the other approaches.

2.3.1.5 Defect Detection Using Cross-Correlation

This method provides an accurate measure of similarity between two images. Any significant variation in the value of this measure indicates the presence of a defect. Correlation is utilized for locating characteristics in one image that will include in another and for that reason supplies a direct and accurate measure of likeness in between two images. Almost any considerable variations in the values of resulting calculations demonstrate the entity of the faults.The cross correlation method in [54] yields adequate results when inspecting imperfections in regularly textured. Otherwise, irregularity textured backgrounds do not correlate effectively and indicate a restriction of this method.

Bodnarova et. al. [55] have applied the correlation coefficient from multiple templates to create a correlation mapfor defect expression. The correlation approach shows to have adequate precision, sufficient sensitivity, specificity and real-time implementation that further effort in algorithm development. These algorithms need to rigorous testing against multiple fault types on multiple backgrounds, and, as the fabric faults is low, achieving useful test predictive values need that the algorithms have majorly low false alarm rates.

The correlation approach in Bennamoun and Bodnarova [56] have provided significantly results when detectingimperfections in regularly textured backgrounds. On the contrary, randomly structurebackgrounds do not adjust well and indicate a limitation and false alarm of that approach.

2.3.1.6 Defect Detection Using Gray-Level Statistics

Independent categories of image pixels, as utilized in [56], is probably to perform badly because locally there cannot be enough information to make good choices on the low contrast faults. Thus, most blemish determination algorithms apply some form of smoothness either precisely before the thresholding.

Tsai and Tsai [57] have suggested the use of a color ring-projection algorithm for computational easily. In experimental results proposed color ring-projection correlation method performs for highly regulartextures such as man-made textile surface and machined surfaces.

The main advantage of this method [58, 59, 60] is their computational easily, that makes them charming for implementation utilizing a basic common purpose computer. Nonetheless, the utility of the process proposed in [61] for on-line fabric detection is low as the delivery time for 256 × 256 pixels has determined for being greater than a minute. On the other hand, the technique does not have any automated technique of choosing thresholds.

2.3.1.7 Defect Detection Using Thresholding

Thresholding is one of the most important process of image process. Especially, it is used to determine close and distinct areas of objects in image. It includes the arrangement of the image separated by pixels until binary structured image. Simply, thresholding process is the process which pixel values on the image are thrown out according to a determined value and other value, values are placed instead of that. Therefore; being taken out of back-ground plan and construct of objects of images on image are provided [62] [63] equation 2.1.

$$U_2 = \left(\alpha + \beta \left| I - I_{mean}^{background} \right|\right) \mathrm{E}_{r,background}^2$$
$$\alpha, \beta \in \Re,\ \alpha, \beta \geq 0 \qquad \text{equation 2.1}$$

Utilization of gray level thresholding provide to determine high contrast faults. This event of a fault reasons the signal level to increase or decrease locally; the presence of a hill or hole after that demonstrate a defect. That defect is determined when the signal crosses a result threshold. Theses methods are used to fabric fault determination [64, 65] on moving textile web. The fault determination can be influential although when the webs are covered by a fine and complex film.

Stojanovic et al. [8], have investigated an automatic vision based system for quality control of textile surfaces and depend on the improved binary, textural and neural network algorithms the suggested method gives good results in the inspection of many types of fabric faults under real conditions. A high fault detection rate with good localization accuracy, low rate of false alarms, compatibility with detection tools and low cost are good advantages of the system as well as the overall detection approach.

The advantages of thresholding method lies in it is ease of implementation. Even so, this kind of method fails to inspect those faults in which appear without changing the mean gray-level in defect-free regions.Additionally this method can be used to detect uni-coloured fabrics without consideration of texture where, the faulty areas are divided into correctly by utilizing two thresholding techniques. Rather than the fact that threshold method is subjective, it has other restrictions; one should ensure that all imaging conditions are always constant and that the non-defective fabric examples are identical. Besides, dirt particles, lint, and lighting conditions on the test sample may create false alarms [28].

2.3.1.8 Defect Detection Using Morphological Operations

The practical utility of the method is restricted as most of generally occurring fabric blemishes are going to be missing from the binary image produced from the basic thresholding operations. Determining faults morphologically about spatially filtered images of fabrics produces better results [66], particularly when the fabric is fine and contains defect of small size.

The statistical morphology allows explaining the geometrical and structural features of an image [67]. In addition, morphological image processing has importance to conditioning, labelling, grouping, extracting, and matching operations on images [68]. Therefore, the morphological operations are executed on a periodic image faults, as opposed to the case in [69] where the entire structure from the thresholded fabric image was used. On the other hand, this method is usually on obvious blemishes and do not suggest any advantage over other obtainable, less complex techniques.

Zhang and Bresee [69] have explained on morphological operations for fabric faults detection. They were used conventional image analysis hardware to image solid-shade, unpattemed, woven fabrics and compared two different software approaches for detecting knot and slub faults in the plain weave and twill weave fabrics.

2.3.1.9 Defect Detection Using Neural Networks

Neural networks are one of the fastest most flexible classifier used for fault detection due to their non-parametric nature and ability to describe complex decision regions. A new method for that segmentation of local textile blemish utilizing feed-forward neural network (FFN) in addition to a new low-cost solution for that task web inspection utilizing linear neural network is presented throughout [70]. The actual usefulness of these two recommended techniques is demonstrated by experimental results acquired from the actual fabric blemishes.

It has been utilized for several years in the producing industry for monitoring and control primarily because of their capacity to learn designs in data from experience (not from specific statistical types of the data). It is supplied when the underlying statistical versions are too complicated or too costly to be designated on traditional means. For small issues neural networks work quite well. Nevertheless, they do not size well to massive datasets [71].

This technique depending on an artificial neural network (ANN) method with 90% perception dependability and a satisfactory computational time [72-81].

Training a neural network can be consume amount of computer time. The output from a neural network is generally difficult to interpret without the use of an expert system. Neural networks are not very good at handling strict statistical calculations and are not suited to applications requiring fast, accurate computations [39].

Hung and Chen [82] have applied neural-fuzzy system for normal fabrics and eight kind of fabric faults. They have combined fuzzy technique with fuzzy logic and a back propagation algorithm with neural networks. back propagationneural network, with fuzzy logic. The result has indicated that the neural-fuzzy system is superior tothe neural network in classification of eight different kinds of fabric faults.

Castilho et al. [83] have presented a real-time fabric fault inspection depend on intelligent techniques. Neural networks (NN),fuzzy modelling (FM) based on product – spacefuzzy clustering and adaptive network basedfuzzy inference system (ANFIS) were used toobtain a clearly classification for defect detection. The results have shown that for real fabric defect detection, the usefulness of the three intelligent techniques and they further stated that NN has a faster performance.

2.3.1.10 Defect Detection Using Fuzzy Logic

The technique described does not practice any kind of thresholding unlike few published techniques which helps to determine each and every edge associated with the image however introduces fuzzy logic which derives its origin from approximate reasoning for high lighting all the edges associated with an image. The fuzzy comparative pixel value algorithm has been developed with the knowledge of vision evaluation with low or no illumination, thus making this, technique for application needing these kinds of techniques.The technique helps to determine edges in an image in all conditions because of subjection of pixel value to an algorithm including host of fuzzy conditions for edges associated with an image.The technique described here uses a fuzzy dependent logic type with the help of that high performance is usually accomplished in addition to simplicity in resulting type.Fuzzy logic helps to deal with problems with imprecise and vague information and thus helps to create a model for image edge detection as presented here [84] displaying the accuracy of fuzzy methods in digital image processing [85].

The fuzzy conditions help to analyze the relative values of pixels that is existing in case of presence on an edge.Therefore the relative pixel values are component inside removing all the edges connected to an image.[86]

There are two systems with regard to determining and classifying fabric blemishes. The first process is depend on fuzzy clustering utilizing fuzzy c-means clustering (FCMI).The other process is Adaptive Neural-Fuzzy Inference System (ANFIS). For each process, three networks are made.The first network receives the tonal characteristics, the other network receives the structure characteristics and the next network receives both tonal and structure characteristics [22].

2.3.1.10.1 Defect Classification Using Fuzzy Clustering

Fuzzy c-means (FCM) is a dataclustering method in where every data point belongs to a cluster to some degree that is specified by a membership grade. This method was initially introduced by Jim Bezdek throughout 1981 [87] as an improvement in before clustering techniques. It provides a technique that will demonstratesto group data points that populate some multi dimensional space into a specific number of different clusters.

FCM begins by having an initial imagine to the cluster centres, which can be intended to mark the mean area of cluster.The initial imagine pertaining to these cluster centres is probably incorrect. FCM assigns every single information point a new membership grade for each and every cluster.By iteratively updating the cluster centres as well as the membership levels for each and every information point, FCM iteratively techniques the cluster centres for the "right" area within an information arranged.Thatiteration is dependent on reducing an objective function that will represents the distance by almost any given information point to a cluster middle weighted by that will information point's membership grade [22].

2.3.1.10.2 Defect Classification Using Adaptive Neuro-Fuzzy Inference System (ANFIS)

ANFIS is usually a class of adaptive multi-layer feed-forward systems that can be functionally equivalent to a fuzzy inference system. It was suggested in order to formalize a systematic method to generating fuzzy rules through an input-output data set.

Texture characteristics seem to be a larger percentage of accurate perception and category in comparison with tonal characteristics for FCM method.

- Tonal characteristics seem to be a larger percentage of accurate perception and category in comparison with texture characteristics for ANFIS method.
- FCM and ANFIS classifiers provide large percentage of accurate perception and category when utilizing both tonal and texture characteristics.
- ANFIS provides very high percentage of accurate category in comparison with FCM [22].

2.3.1.11 Defect Detection Using Eigen filters

The data written content of defect-free fabric image may also be taken out by enrolling the variations in an ensemble of macro windows in the image, unbiased of any judgment of it is structure. The eigenfilter-based approaches are useful within removing pair wise linear dependencies, in lieu of larger order dependencies, between image pixels. The key info in most fabric textures is in higher order relationships amid image pixels. Therefore, fabric blemish perception using unbiased part evaluation (ICA) of fabric structure has been recommended within [88].On the other hand, these appearance-based approaches using eigen filters or ICA usually are highly responsive to regional fabric distortions along with backdrop disturbance, and they are consequently not interesting intended for online fabric inspection. Nevertheless, the eigen filters or ICA are extremely sensitive to local fabric distortions and back-ground noise, and are consequently not attractive for on-line fabric inspection. (ICA) has really low real-time computational requirements, since the on-line part of the computations requires just a easy matrix multiplication. That provides great perception results with 96-97%.

Monadjemi [89, 90] has proposed by structurally matched eigenfilters, through rotation, negationand mirroring, for textured fault inspection. The method is 90 % accuracy, fast and full potential for real time implementation. The most important advantage is low dependence on negative samples.

2.3.1.12 Defect Detection Using Histogram

Histogram is the graphicalexpression of values of pixels on the image. This is called as image histogram or gray-leveled histogram [62]. Image histogram shows determination of pixel in each points and how much numbers of the pixel are. So, it is provided that several information related to image on the histogramis taken out. The pixels on image are exactly taken out where they are placed.

Histogram and the rank function provide exactly the same information. The colour information in textured images can also be used to extract colour histograms and this has been used in [91, 92] to detect defects.Histogram investigation is done rather than a point-to-point investigation. Since different images normally become more comparable one to the other after histogram equalization, since their lighting and contrast tend to be more related, equalization is usually executed. On many occasions, histogram equalization offers an image along with structural detail that is much more apparent for the human eye than original image regions in which smaller lighting gradients exist.

Zhang and Bresee [93] have utilized histogram equalization in which reassigns grey level values of pixels to obtain much more uniform grey level distribution in an image. During this method, individual pixels preserve their lighting order, however more flattened histogram can be produced so the lighting and contrast of images are changed.

Thilepa [94] has utilized noise filtering, histogram and thresholding approaches utilizing Matlab to inspect fabric faults along with 85% all round productivity. Despite their easily, histogram methods have demonstrated their low cost and high perception accuracy [28, 41].

2.3.2 Spectral Approaches

These are generally powerful and also efficient computer-vision techniques for fabric blemish detection. In this techniques structure is usually characterized by texture primitives or texture components, and the spatial arrangement of these primitives [94]. So, the main aims of these techniques are primarily to get texture primitives, and thenext generalise the spatial positioning rules. The high amount of periodicity of standard texture primitives, such as in the case of textile fabric, permits using spectral features with the determine of blemishes. Nonetheless, randomlytextured images cannot be explained when it comes to primitives and also displacement rules as the submission of gray levels in such images is quite stochastic. Therefore, spectral techniques are not proper for the actual detection of blemishes with randomly structure products. Throughout spectral- domain techniques, the particular texture features usually are divided the Fourier transform [96, 97], Optical Fourier Transform, Windowed Fourier Transform, Gabor transform, Optimized Fir Filters, Wigner Distributions [98, 99] and also Wavelet transform [100].

2.3.2.1 Defect Detection Using Discrete Fourier Transform

Fourier transform has the desirable properties of noise immunity, translation invariance and the optimal characterization of periodic features. The FT characterizes the textured image in terms of frequency components. The periodically occurring features can be observed from the magnitude offrequency components. These global texture patterns are easily distinguishable as concentration of high-energy bursts in the spectrum.

Literature studies have presented that Fourier analysis is used to determine for only errors of fiber. This analysis does not give any information about type and place of errors. Supervisor only notices error after analysis of image, but he/she can not get information about error.

The woven fabric image is a combination of warp and weft yarn patterns. Each of these yarns is effectively 1-D and may be modeled by a comb of impulses that are modulated by the profile of one yarn [15]. Because of the stochastic textured components on the real fabric images, the local maxima peaks in the 2-D frequency plane are not properly localized.

Chan and Pang [6] studied about errors on warp by comparing spectrum draw of defectable and in defectable images in weaving fibers. Study results show that normalized size of united spectrum draw a broken yarn to both warp and scarf can be determined with upconverter in spectrum.

Another study used Fourier analysis was made Tsai and Huang [101], focusing errors on several weaving surfaces. This study has been showed that repeated figure can be eliminated by taking small circular samples from Fourier spectrum images and evanishing frequency component in, out and center of circle and trying to emphasis available errors.

Escofet et al. [102] have appliedthe angular correlation of the Fourier spectra to automatically evaluate fabric surface resistance to abrasion and compared two images of fabric samples and investigated to help for the objective and automatic fabric fault inspection.

Campbell and Murtagh [103] have described the implementation of fabric defect detection methods for woven fabrics and a Windowed Fourier transform based method to inspect faults on denim fabric samples. The results of this study shown that proper false alarm rate with the credible inspection of faults.

Fourier analysis is proper for situation that error generally spoils material; but it does not give information about position and figure of errors. Therefore, this analysis takes only frequency information from original image; because it does not obtain spatial information lose value. additional algorithms are needed to determine limited errors by depending on original images. So, Fourier analysis is not much preferred method. [32].

To apply Fourier analysis for fabric fault inspection, various techniques can be obtained; Optical Fourier Transforms (OFT) acquired in optical domain by utilizing lenses and spatial filters can be utilized, however most methods, digitally implemented, are derived from Discrete Fourier Transforms (DFT) and/or its Inverse (IDFT) which recovers the images in the spatial domain: typical Fast Fourier Transforms (FFT) or Windowed Fourier Transforms (WFT) variants which are able to localize and analyze the characteristics in spatial as well as rate of recurrence domain.

2.3.2.1.1 Defect Detection Using Optical Fourier Transform (OFT)

The Fourier transform of textile fabric can also be procured with optical domain by utilizing lenses in addition to spatial filters. Thus, the detection of textile blemishes applying OFT is relatively simple as well as rapid. Fraunhoffer diffraction structure of a object (fabric) isthe Fourier transform of this object [104]. The luminous intensities of the zero and first-order diffraction designs are generally modulated from the existence of fabric blemishes [105]. So this fabric fault detection systems using measurements ofthe first and the zero-order intensities have been improved. The actual diameter of a laser beam used to create OFT images of the moving fabric cannot betoo wide general the spacing of the weft and the warp yarns in the fabric. The small beam diameter acquires multiple optical systems [106] to include the width on the fabric that is expensive and intricate.The OFT images are not just useful for the inspection of fabric faults but also for their classification.

Ciamberlini et al. [107] have explained the design of spatial filters and Fourier transformation adaptable for different types of fabric structure for the fault inspection in the textile surfaces in real time.

2.3.2.1.2 Defect Detection Using Windowed Fourier Transform (WFT)

Inspection of local faults demands techniques that may localize and analyze the characteristics and so that, characteristics depend on space-dependent Fourier transform or running-window Fourier transform or WFT have been recommended for fabric fault inspection.

Fault determination techniques depend on DFT and OFT are insufficient when the position of faults, i.e, spatial localization. Furthermore, the small or the local defects may be warped in the inevitable averaging that takes place in the feature estimation of large image regions. So, this DFT- and also OFT-based techniques are suitable for generally blemishes in lieu of community blemishes. Detection of local defects requires the techniques that can localize and analyze the features in spatial as well as frequency domain. For that reason, features based on space-dependent Fourier transform or running-window Fourier transform or WFT have been suggested for fabric defect detection.

Campbell et al. [108] have explained the implementation of a texture fault inspection method for the woven fabrics and indicated feature extraction using windowed Fourier transform and than decision mechanism has the potential for parallel implementation through a FFN. They have computed WFT features in a 32 $\times$ 32 pixel moving windows to inspect denim fabric faults

2.3.2.2 Defect Detection Using Gabor Filter

Gabor filters is another decomposition method used in signal process. Data type is remarked by being passed Taken images from differentiated Gabor filter according to aims. So, Gabor filters hascommonly been used in error determination and computer image process areas recently.In this point, Gabor filters have found usage in the determination of errors in textile products and places on error. With Gabor filters, both place and type of error and determination of error can be found like Fourier analysis.

The impressiveness of WFT-based approaches has indicated the substantial of the conjoint analysis of the textured images in both of spatial and rate of recurrence fields. Thus, the texture properties that signify the rate of recurrence content in localized areas in the spatial domain have captivated the interest of several researchers. These properties might be taken from the inspection images by the localized spatial selection. The 2-D Gabor filtration are suitable for this spatial selection in lots of senses [108]: they have tunable angular and axial rate of recurrence bandwidths, tunable centre frequencies, and achieve optimal combined solution in spatial and rate of recurrence domain. The variables of a Gabor filtering might be selectively optimized to discriminate a new recognized group of blemishes. Like segmentation of fabric faults utilizing best or optimal Gabor filters have been indicated. The sizing and alignment of regional blemishes made on the textile web varies randomly. Thus, a general web assessment technique utilizing a bank of symmetric and asymmetric Gabors filters have been informed in [110], [111], [112] and [113], respectively. The mechanism of texture segmentation in human visual systems have been explained with the Real Gabor Functions (RGFs) along with the sigmoidal shaped nonlinearity in the retinal changes. So, the bank of multiorientation and multiresolution RGF, accompanied by intra and interscale image blend, is advised to section fabric faults [114], [115].

Hou and Parker [116] have examined defect detection methods on textile surfaces by using Gabor wavelet features and an adaptive filter selection was applied to reduce the computational cost on feature extraction. In experimental results demonstrate, this method can successfully localize and divide faults in texture images.

Kumar and Pang [114] used a set occurring from several dimension and orientation 16 Gabor filter. They determined the most proper filter according to size, orientation etc.

Of fiber by using a managed sectioning algorithm and they showed that this system is active for changing dimension and orientation.

2.3.2.3 Defect Detection Using Optimized Fir Filters

Several fabric faults that will make very little strength changes might be difficult in order to determine using the other spectral techniques. Some sort of probable way to the determination of such blemishes is to utilize ideal finite impulse response (FIR) filters.The optimisation proposes the latent of significant element separation between the faultless and the faulty areas of the filtered image. The Gabor filters and the infinite impulse response (IIR) filters are the filters using just a few free variables and then the search area for optimization can be quite limited. Better optimisation benefits can be acquired when the amount of free available variables of any filtration system is actually significant. An over-all FIR filtration system offers more free variables than when compared with an IIR or Gabor filtration system and therefore supplies the benefit of computational simplicity.The perfect FIR filters utilized for fabric fault determination in [117], [118] demonstrate high detectionof very simple faults and uncontrollable examination using a bank of such filters.

2.3.2.4 Defect Detection Using Wigner Distributions

The Wigner distribution function is Fourier-like however has been shown to provide better conjoint resolution than Gabor or Gaussians for conjoint spatial and spatial-frequency image representation. The fabric fault detection techniques applying optimal FIR filtration systems and Wigner distributions have been indicated to be very effective to determine a types of fabric faults. But, the utility for unsupervised web supervision, within simultaneously determination of faults from a large number of classes, is yet to be indicated.

This algorithm is beneficial as soon as executed for on-line fabric fault detection however its computation time is prohibitive. Nevertheless its utility for unsupervised fabric inspection, at the same time percepting blemishes a lot of classes, is actually but to be shown. The major disadvantage in this method [15] may be the existence of interference terms between the different aspects of the image.

Song *et al.* [119] have presented an alternative algorithm that using with Winger model to describe cracks in complex textural and investigated the windowing features of the winger distribution and their effect on crack inspection. They have indicated the local crack information is best encapsulated in the shape of the spectrum. The results shown that the winger model has better discriminatory power than the short time FourierSpectrum and the algorithm has produced very good results for a 256 x 256 granite image.

2.3.2.5 Defect Detection Using Wavelet Transform

Wavelet transforms method shows similar features with Fourier analysis. However, while processed analysis in Fourier analysis is decomposing to sinusoidal, signals in the method of wavelet transformers are parted to small wavelet. Being parted of Signals which will be processed gives place of data and data wanted in that signals to supervisors. In thepoint of error of fiber,it is determined where defective part in processed image exactly is being chosen proper wavelet and what type of error is with wavelet transformers.In recent years, multi resolution decomposition plans depends on wavelet transform have received considerable relevance while options for the removal of textural features. The multi-resolution wavelet representation enables an image to be separated into a pecking order of localised sub images at different spatial frequencies. It divides the 2D rate of recurrence range of an image into a lower pass (smooth) sub image and a set of high pass (detail) sub images. The textural features are usually then taken out from the decomposed sub images in different rate of recurrence programs and various resolution levels. The multiscale wavelet performance property of shift invariance and also can be utilized for fabric fault determination by examining fabric images at different scales[120].

Ngan et.al. [121] have improved the use of the wavelet transform an automated visual detection method for fault inspection on patterned fabric. The method of wavelet pre-process golden image subtraction (WGIS) has developed for fault inspection on patterned fabric.They have demonstrated the WGIS method has the best fault detection results and accuracy is 96.7 % with 30 defect free images and 30 defective patterned images for Jacquard fabric.

Sari-Sarraf and Goddard [5] studied on activity of a wavelet based on error determination system. In their study, they used Daubechies as wavelet in determination system. Their study proposes two dimension four core,composing high pass (HP) and low pass (LP). This filter combination, placed with proper parameter nearly reacts zero reaction to a faultless fiber image.

2.3.3. Model-Based Approaches

Texture is often thought to be a complicated pictorial design and can be described by the stochastic or a deterministic type. But, the actual textures, for instance fabrics, can be combined with stochastic and deterministic components. The actual textures is usually patterned as stochastic processes, and textured images is usually observed as the realizations or the actual samples from parametric possibility distributions on the image area [122]. The benefit of this modeling is that it can easily produce textures that can match the actual observed textures. The blemish determination problem is usually processed as being a statistical hypothesis-testing problem about the statistics produced from this model. Model-based methods are generally specially suited to fabric images together with stochastic surface area variants (possibly fiber pile or noise) or for randomly textured fabrics for which is the statistical and spectral method have not yet demonstrated their utility.

2.3.3.1 Defect Detection Using Gauss Markov Random Field (GMRF) Model

Approach of Markov Rassal Areas express that provides image a random image, the brightness level of a pixel depends on brightness level of neighbour pixel as related to images [3].

In the view of determination, of errorin textile products, this method can be used in the following:

1. Image of faultless fiber is separated to areas of pixel.
2. One of areas of pixel is taken average comparatively with other areas.

Taken average will be same with average of prime taken pixel area if the fiber is faultless. However, if fiber has faultless average of pixel areas where indefect is, will be different. This shows an error in image and place of error to supervisor. But it does not give information about type of error [1].

The model of Markov Rassal Areas cannot be thought as a good mean about the subject of definition approximately place of error by comparing with taken image. This method gives some spatial information about type of error because it shows activity in determination of error. A feature extractor is needed to perform sectioning of error in filtered image. The methods uniting determination and sectioning of error in one filter is more effective than the models of Markov Rassal Areas [1]. Markov random fields utilize an exact type of this dependence. They are able to capture the local (spatial) contextual details in an image. These designs suppose that the intensity at each pixel in the image based on the intensities of just the neighbouring pixels. The idea offers a convenient and consistent way for modelling context primarily based entities for example pixels.The stochastic types depend on the GMRF have been efficiently indicated to type many natural with man-made textures. [123].

Özdemir and Erçil [33] have studied on amodel based approach with Markov Random Fields (MRF) as the texture model and a new method based on Karhunen-Loeve Transforms for the defect detection of textile fabrics. Both methods seem to be successful in finding defects in textile fabrics.Besides, the MRF method seems to be much faster than the Karhunen-Loeve Transform based approach.

Baykut and others [3] have investigated errors and applied this approach same fiber images with the aim of determination of errors of a fiber. Taken image has been parted to many Windows and filter has been applied to each window.From this point, a possibility statistic was calculated for each window and was be compared with statistic of original fiber. If these statistical values are not harmony with each other in some confidence level, the window under investigation has an error.

2.3.3.2 Defect Detection Using Poisson's Model

The stochastic types of some of the randomly textured materials which have been produced in the industry are depend on the nature of the manufacture method. One of these regarding this kind of material will be the fibrous, nonwoven material procured by melt blowing polypropylene resin and used for air filtration.

Brazakovicet. al. [36, 38] have described designing and testing system for inspection of web materials using a development environment simulated in software. They have discussed a theoretical approach based on Poisson's model, its efficient implementation, and steps required to implement this procedure off-line.

2.3.3.3 Defect Detection Using Model-Based Clustering

The situation of locating achievable clusters in the information (image) is often a recurrent one with a long history. This approach is extremely good for all colour images. On the other hand, the performance seriously is not satisfactory when the image is dominated by gray colours.

Campbell et. al. [124, 125] have combined image-processing techniques with a powerful new statistical technique to detect linear pattern production faults in woven textiles. The model used in experimentation is a possibly highly elliptical. Gaussian cloud superimposed on Poisson clutter. Results are shown for some representative examples, and contrasted with a Hough transform. Software for the statistical modelling is available.

CAPTER 3

RESULT AND DISCUSSION

In previous chapter, General Information related to all image processing method applied to determine error in detail. In this chapter, a table including particular features of methods told in previous chapter (suitable for fabric, fault magnitude, accuracy, computational time and algorithm density) has been prepared.

According to the table, although Matrix Method is proper for all fabric, it has not been chosen, because it is not proper for computational time and algorithm density.

Although Local Linear Transforms method is applicable for small dimensioned errors as fault magnitude , it has not been used because its accuracy and computational time features is not good.

Because Fractal dimension method is used to determine big error types as a type of fault magnitude and its accuracy is bad, it has been eliminated directly.

Because cross correlation method is used to determine big error types as a type of fault magnitude, it has been eliminated directly.

Gray-level Statics method has not been preferred because it is used to determine big error types as a type of fault magnitude and its accuracy and computational time is bad.

Although Neural Networks method has much good features in the view of accuracy and computational time feautures, it has not been preferred because it is used to determine big error types as a type of fault magnitude.

Altough Fuzzy logic method determine all type of errors, it has been eliminated because its computational time feature is not good.

Although Eigen Filter method is applicable in small dimensioned errors as a type of fault magnitude, it has been eleminated because its accuracy feature is bad.

Because Histogram method gives graphical results in the determination of error, it has not been proper to use in our studies.

Because Fourier transform method is used to determine big error types as a type of fault magnitude, it has been eliminated because its accuracy and computational time is bad.

Although optimized fir filter method determines all type of errors it has been eliminated because its compuatational time feature is not good.

Although wavelet transform method determines all type of errors, it has been eliminated because its computational time feature is not good.

Although Gauss-markov method determines all type of errors, it has been eliminated because its accuracy feature is not good.

Poissonion method is used for nonwoven fiber. Because of tissue and surface differences between weaving and nonwoven, it has not been seen proper to be used in our studies.

Although based clustering model determines all type of errors, it has been eliminated because its accuracy feature is not good.

Table 3.1 Properties of Defect Detection Methods

Properties						
	Approaches	**Suitable for fabric**	**Fault Magnitude**	**Accuracy**	**Computational time**	**Algorithm Density**
Statistical	**Matrix Method**	Suitable	All	Good	Weak	Complex
Statistical	**Local Linear Transforms**	Suitable	Small	Moderate	Moderate	Complex
Statistical	**Fractal dimension**	Suitable plain	Large	Low	Moderate	Basic
Statistical	**Edge Detection**	Suitable Plain fabric	Large	Good	Moderate	Basic
Statistical	**Cross-correlation**	Suitable	Large	Moderate	Moderate	Complex
Statistical	**Gray-Level Statistics**	Suitable	Large	Weak	Weak	Basic
Statistical	**Thresholding**	Suitable Plain fabric	Small	Good	Good	Basic
Statistical	**Morphological Operation**	Suitable Plain fabric	Small	Excellent	Excellent	Basic
Statistical	**Neural Networks**	Suitable Plain and twill fabric	Large	Excellent	Good	Complex
Statistical	**Fuzzy Logic Method**	Suitable Plain fabric	All	Moderate	Moderate	Complex
Statistical	**Eigenfilters**	Suitable	Small	Good	Weak	Basic
Statistical	**Histogram Method**	A graphical Method (cannot be used alone)	All	Moderate	Good	Complex
Spectral	**Fourier Transform**	Suitable for Plain fabric	Large	Weak	Low	Complex
Spectral	**Gabor Filter**	Suitable Homogeneus and jacquard	All	Good	Weak	Complex

		plain denim twill fabric				
	Optimized Fir Filters	Suitable	All	Moderate	Moderate	Basic
	Wigner Distributions	Suitable	All	Moderate	Excellent	Complex
	Wavelet Transform	Suitable Plain Twill Patterned Fabric	All	Good	Moderate	Complex
Model-Based	**Gauss Markov Model**	Suitable	All	Weak	Moderate	Complex
	Poissonian Model	Suitable for Nonwoven	Small	Moderate	Moderate*	Complex
	Model-Based Clustering	Suitable for Denim Fabric	All	Moderate	Poor	Complex

(For fault magnitude parameter; Small, Medium, Large.For other parameters; Poor, Weak, Modorate, Good, Excellent)

Also, in this chapter, finally the methods being used by us in our studies in the result of examination has been determined and explained in detail.

Among the all methods, four image process methods are determined as suitable candidate for on line image processing application. These four image process methods are explained in details in this chapter. In order to apply image analysis practically, two line scan cameras with 8192 pixel resolution and a professional light source have been used to obtain the images. Cameras have been spaced by distance of 1 meter from fabric. Besides, in the experiment, one meter length white led light source has been used. The distance between the light source and fabric is 12-13 cm[126].

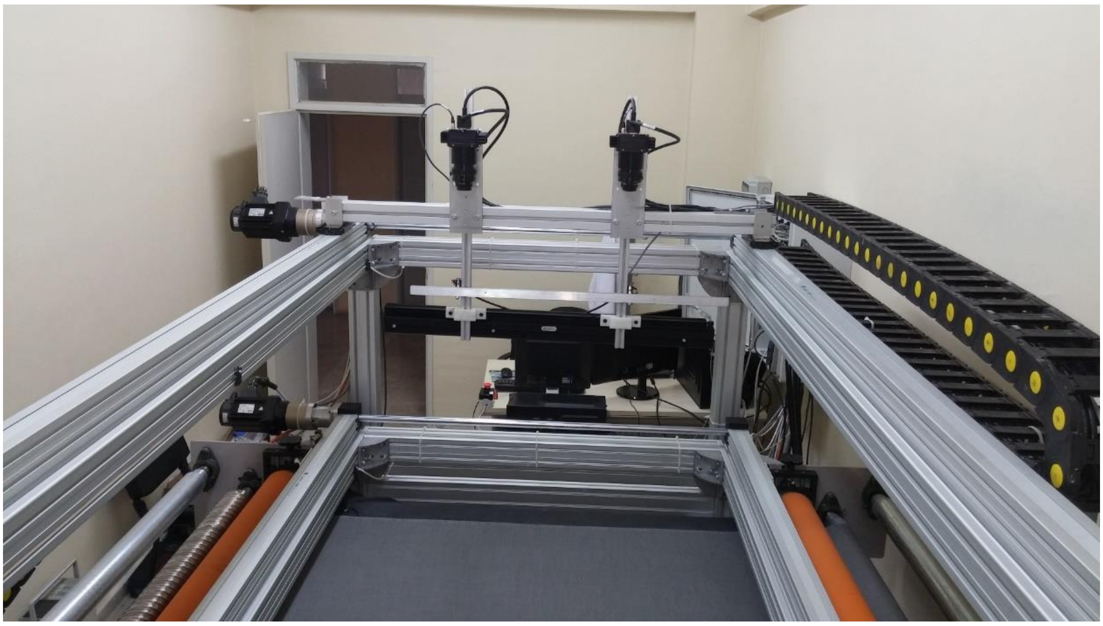

Figure 3.1 The experimental setup used in the thesis

In the stage of made prior review, by using **Morphological Operations, Threshold Operations, Gabor Filter Operations, Wigner Distributions Operation,** application results have been obtained.

3.1 Morphological Operations

According to table, morphological operation method has been preferred in the determination of small errors, because its accuracy feature is excellent, computational time is excellent and finally algorithm density is basic. The process steps of this method has been shown in Figure 3.2

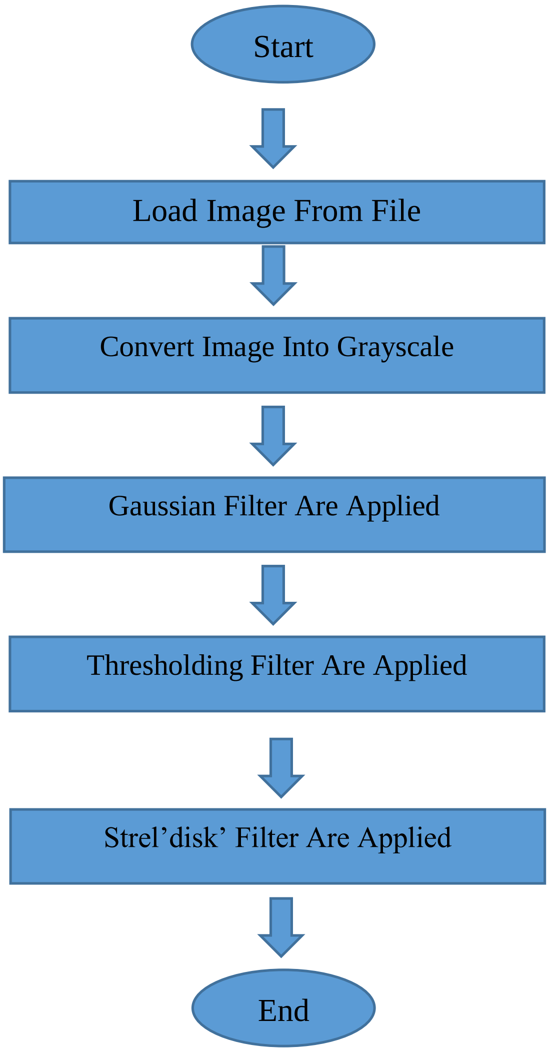

Figure 3.2 Morphological Operation of flow chart

1- Colour Correction: this process is necessary to reach wanted level to brilliance and contrast of images. Black-white format of image has been given in Figure 3.3.

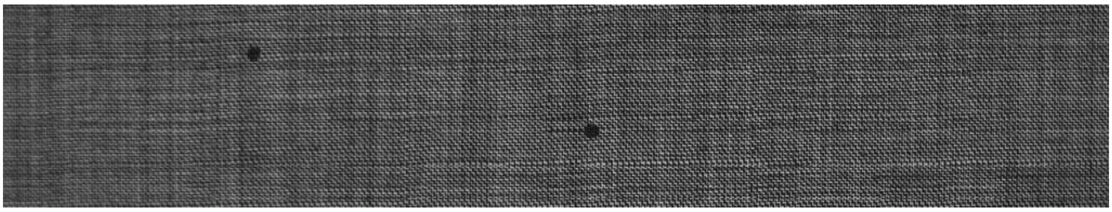

Figure 3.3 The result of black-white image

2- By having subjected to Gaussian filter process the image in Figure 3.3, it enables errors more available. In Figure 3.4, the result of Gaussian filter has been given.

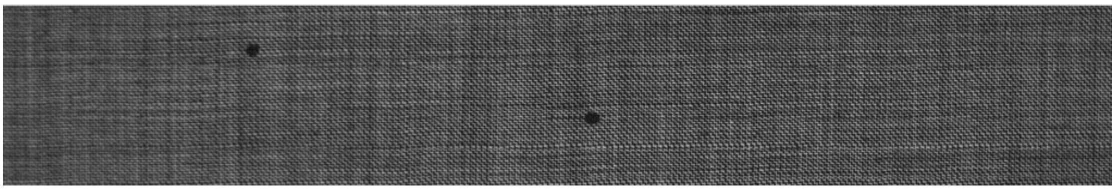

Figure 3.4 The result of Gaussian filter

3- By being applied threshold value process to image in Figure 3.4, image filter is obtained. Image threshold is a simple but affective method parting front and back plan of an image. This image analysis technique is an image segmentation providing insulate of objects by converting gray toned images inside binary images. In Figure 3.5, the result of threshold process has been given.

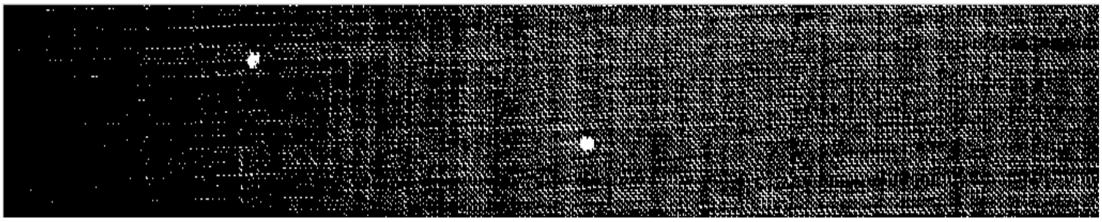

Figure 3.5 The result of Threshold

4- By being applied strel ‘disk’ filtering process to image given in the Figure 3.5, straight disk shaped construct element, known its diameter has been formed.

In Figure 3.6, the result of strel filter process has been given. In Figure 3.7, mark of errors on the original images has been processed.

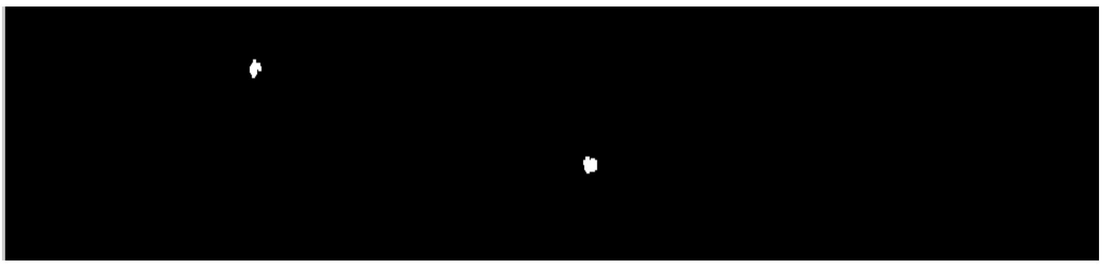

Figure 3.6 The result of Strel ‘disk’ filter process

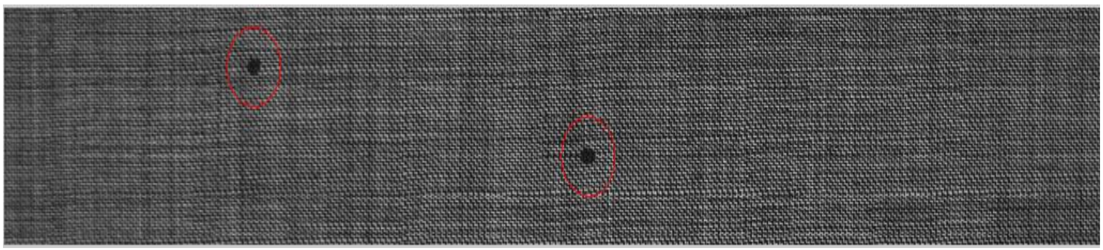

Figure 3.7 Mark of errors on the original images

5- Table 3.2 Output programme indicating coordinates of error and field of image

Table 3.2 Output programme indicating coordinates of error and field information

Number of Faults	X – Axis (Pixel)	Y – Axis (Pixel)	Area (Pixel)
1.	466,95	75,55	300
2.	1092,36	188,95	384

Elapsed Time: 1.41 seconds.

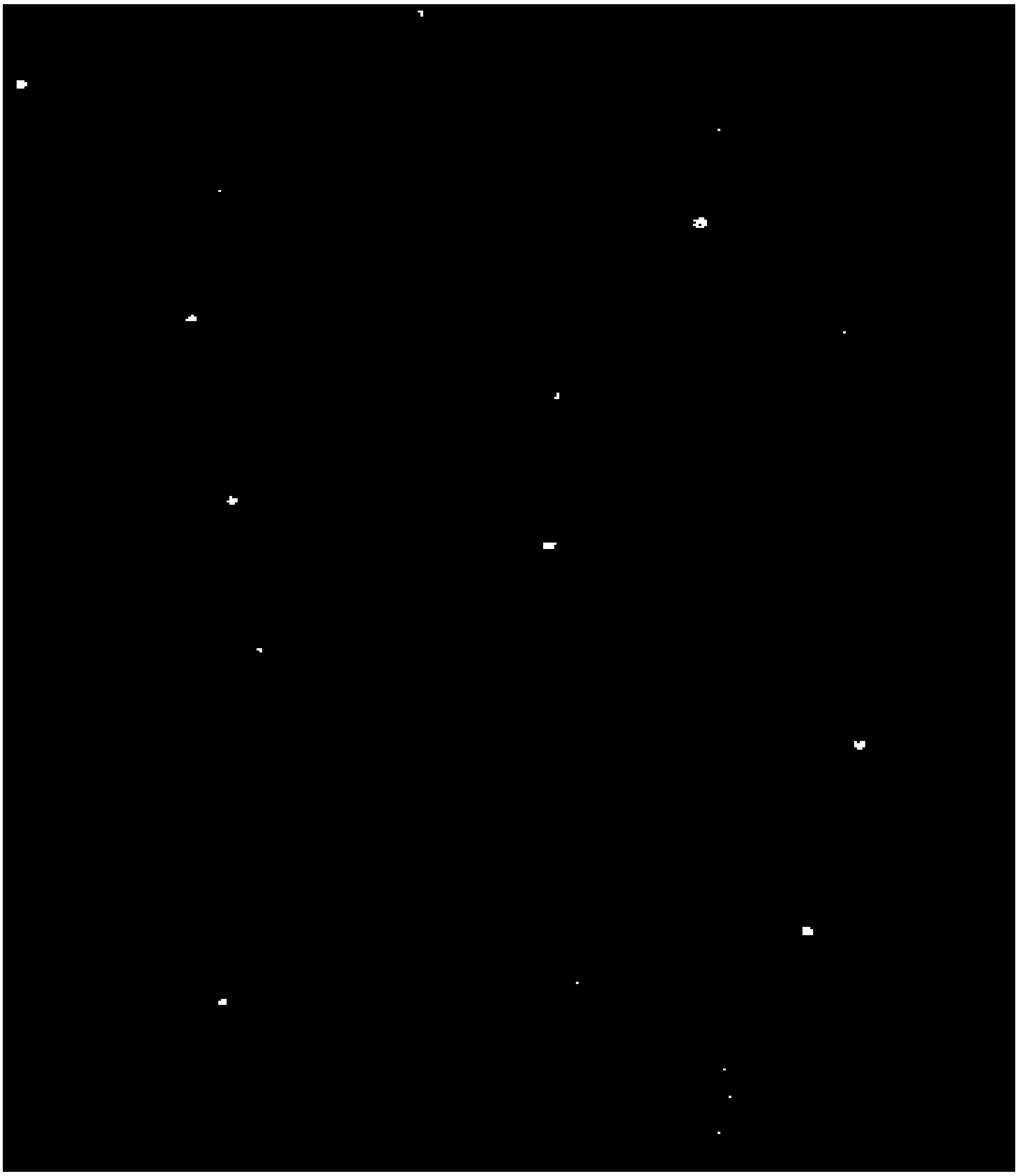

Figure 3.8 The result of image process of united ten several pictures

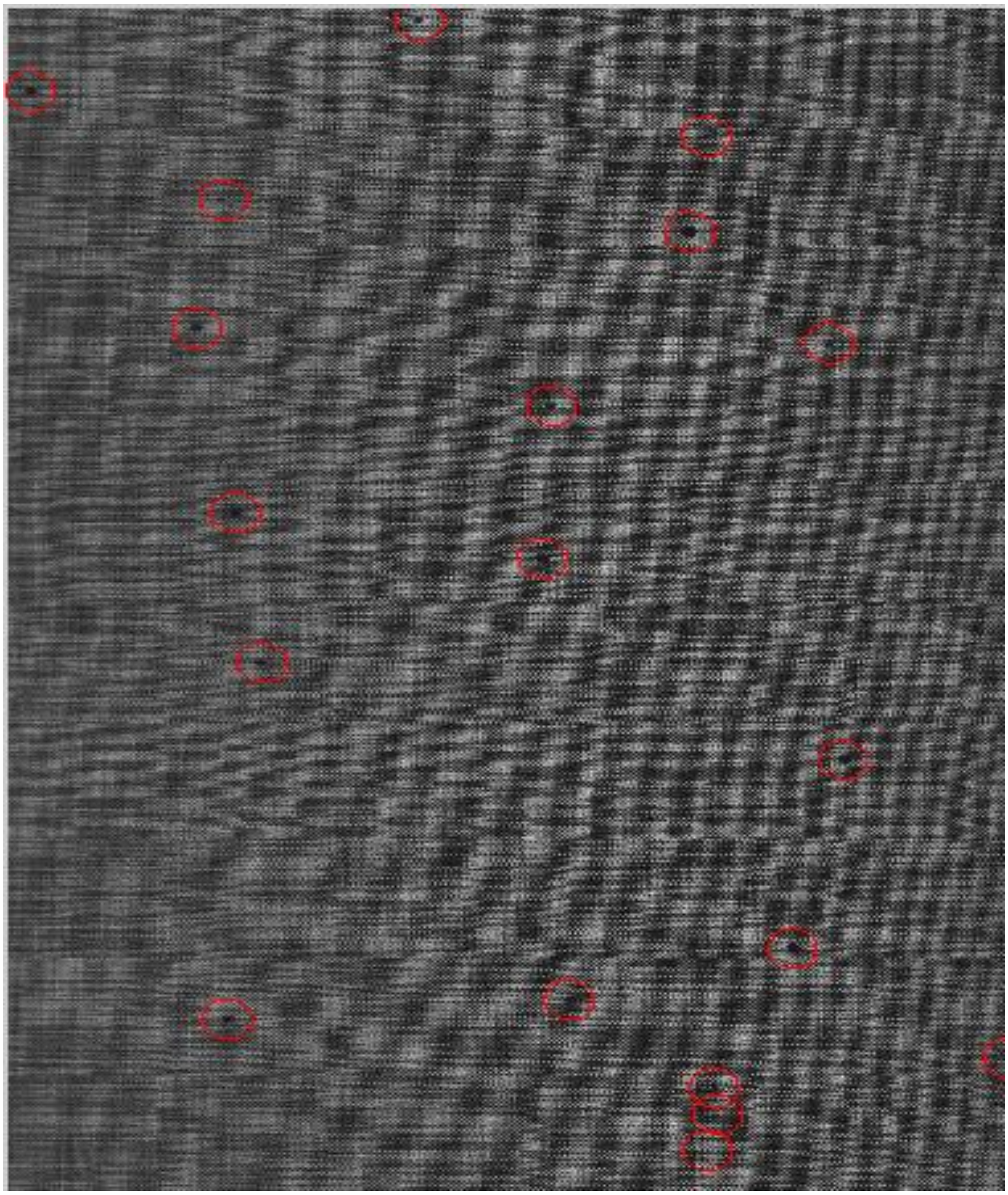

Figure 3.9 Mark of errors on the original images

Table 3.3 Output programme indicating coordinates of error and field of image

Number of Faults	X – Axis (Pixel)	Y – Axis (Pixel)	Area (Pixel)
1.	49,29	210,38	339
2.	386,56	808,74	278
3.	440,07	484,43	41
4.	449,56	2556,62	246
5.	466,95	1275,55	300
6.	519,43	1655,16	73
7.	839,70	29,19	139
8.	1092,36	1388,95	384
9.	1110,02	1005,78	130
10.	1146,50	2507,50	36
11.	1393,27	565,90	583
12.	1427,00	325,00	25
13.	1430,00	2888,00	25
14.	1442,00	2730,00	25
15.	1450,5	2797,00	30
16.	1603,02	2375,98	413
17.	1678,50	847,00	30
18.	1706,37	1899,90	354
19.	2043,00	2657,00	25

Elapsed Time: 5.55 seconds

3.2 Threshold Operations

According to table, threshold operation method has been preferred in the determination of small errors, because its accuracy feature is good, computational time is good and finally algorithm density is basic. The process steps of this method has been shown in Figure 3.10.

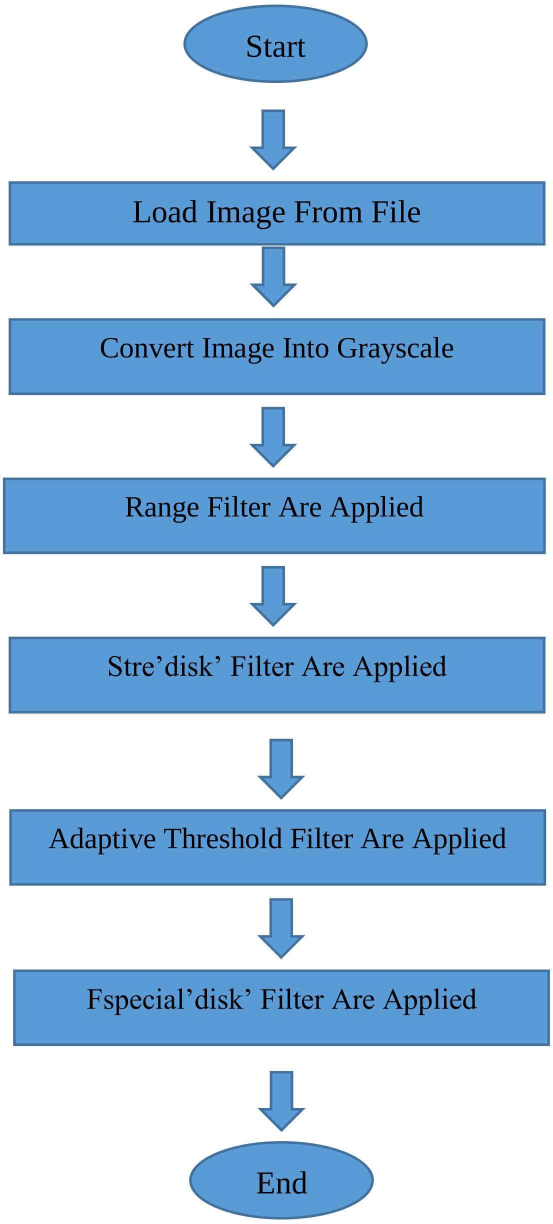

Figure 3.10 Threshold opretation of flow chart

1- Firstly, the process of conversion to black-white format has been applied to image. In Figure 3.11, black-white format of image has been given.

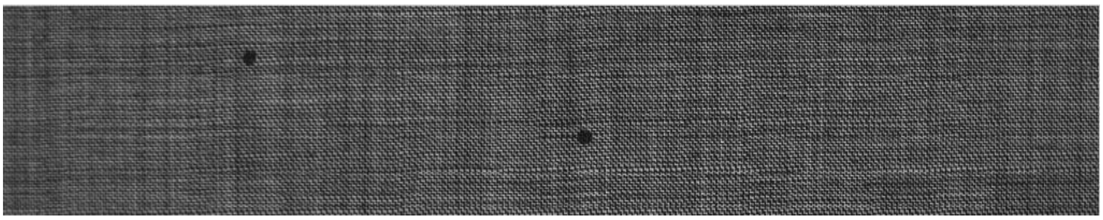

Figure 3.11 The result of black-white format

2- By having subjected to range filter process the image in Figure 3.11 it enables borders and limits of errors more available. In Figure 3.12 the result of range filter has been given.

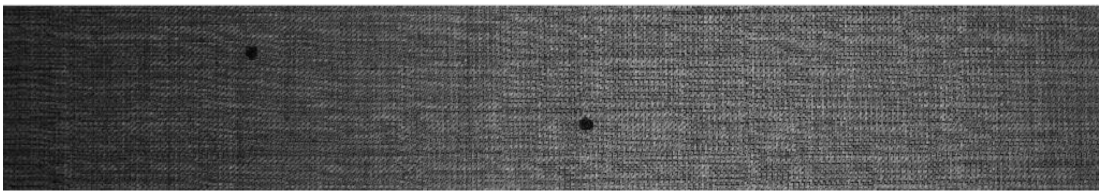

Figure 3.12 The image applied Range filter

3- In later stage, by being applied combination process with original image to Figure 3.12, errors on images has been provided more available. In Figure 3.13 the end of process has been given.

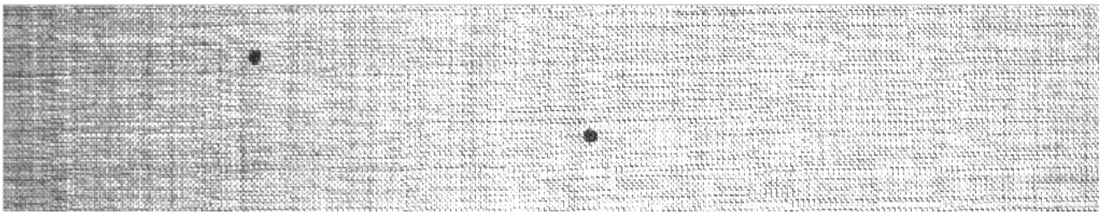

Figure 3.13 The result of combination of corrected and original image

4- In other stage, adaptive threshold process has been applied to the image given in the Figure 3.13. Adaptive threshold is an adaptive threshold algorithm. In this way, being separated front plan from back plan with non-uniform illumination has been provided. In Figure 3.14, the end of process of adaptive has been given.

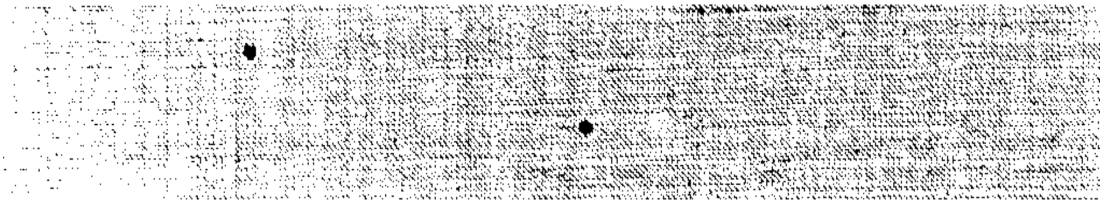

Figure 3.14 The image applied Adaptive threshold

5- By being applied Fspecial 'disk' filtering process to image given in the Figure 3.14, straight disk shaped construct element, known its diameter has been formed. In Figure 3.15, the result of Fspecial 'disk' filter process has been given. In Figure 3.16, mark of errors on the original images has been processed.

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Figure 3.15 The result of Fspecial 'disk' filter process

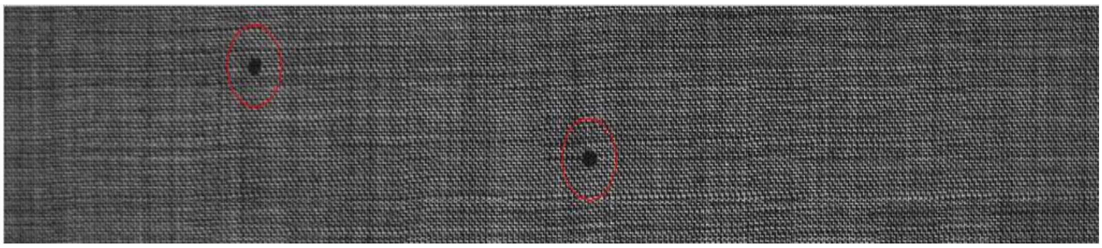

Figure 3.16 Mark of errors on the original images

6- Output programme indicating coordinates and fields of error has been given in Table 3.4.

Table 3.4 Output programme indicating coordinates of error and field of image

Number of Faults	X – Axis (Pixel)	Y – Axis (Pixel)	Area (Pixel)
1.	467,01	74,25	275
2.	1090,69	188,85	394

Elapsed Time: 3.27 seconds.

Figure 3.17 The result of image process of united ten several pictures

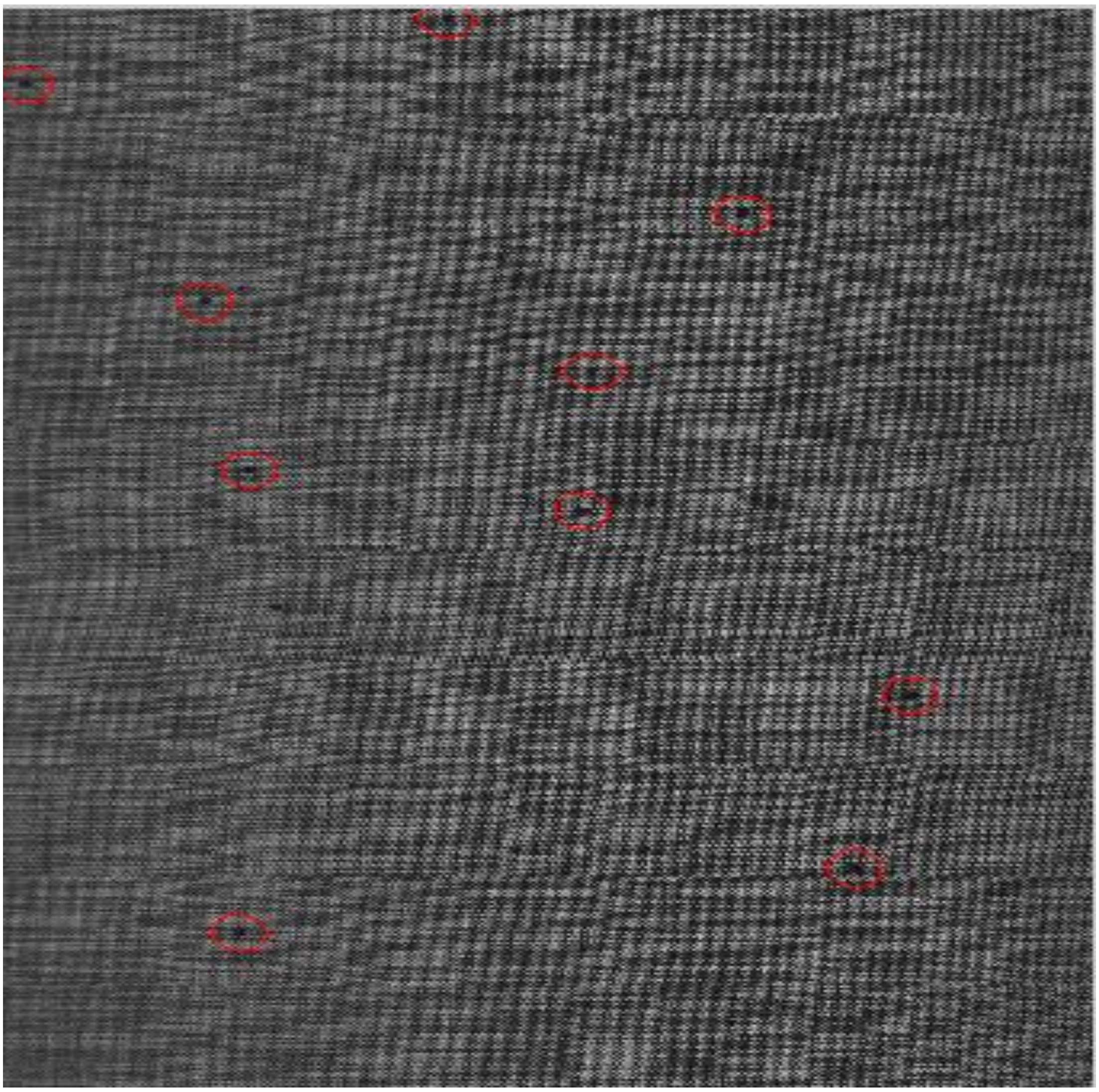

Figure 3.18 Mark of errors on the original images

Table 3.5 Output programme indicating coordinates of error and field of image

Number of Faults	X – Axis (Pixel)	Y – Axis (Pixel)	Area (Pixel)
1.	50,43	210,98	53
2.	385,92	809,67	68
3.	450,14	2556,31	196
4.	467,31	1274,48	245
5.	836,58	28,83	185
6.	1090,67	1388,55	369
7.	1111,61	1002,69	154
8.	1393,76	566,64	779
9.	1602,66	2377,67	475
10.	1706,45	1900,48	451

Elapsed Time: 22.00 seconds

3.3 Gabor Filter Operations

According to table, Gabor Filter operation method has been preferred in the determination of small and big errors, because its accuracy feature is good , computational time is weak and finally algorithm density is complex. Although its features are bad, Gabor filter method has been preferred because working principle of Gabor filter is the same as the principle of human eye in our studies. The process steps of this method has been shown in figure 3.19.

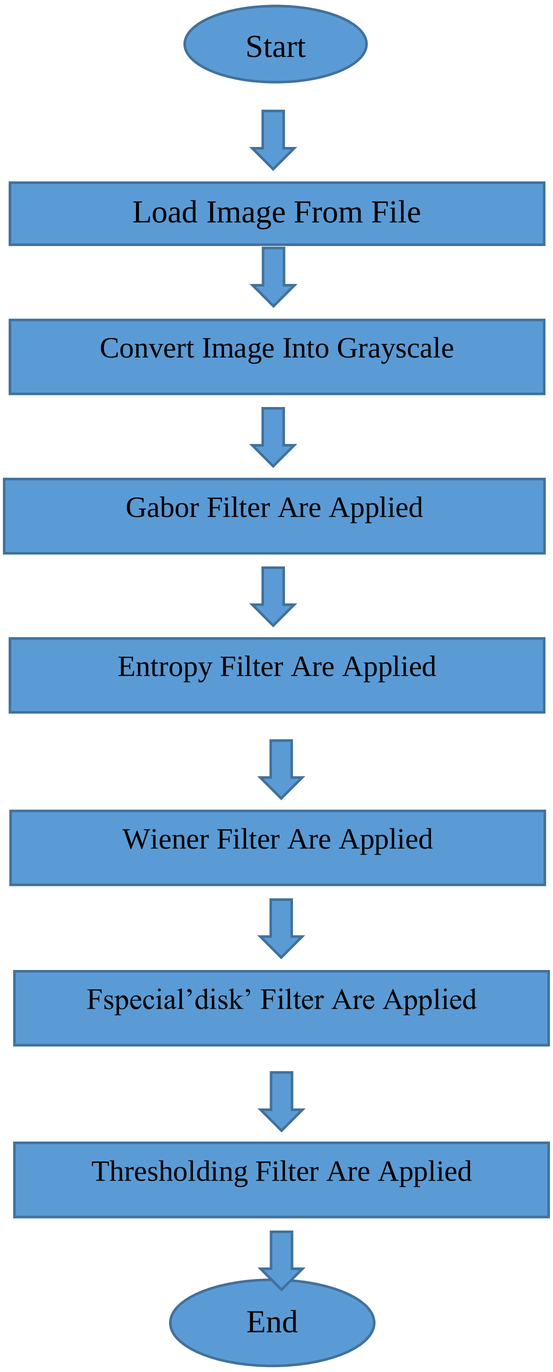

Figure 3.19 Gabor Filter Operation of flow chart

1- Colour Correction: this process is necessary to reach wanted level to brilliance and contrast of images. The original image has been given in Figure 3.20 and corrected image in Figure 3.21.

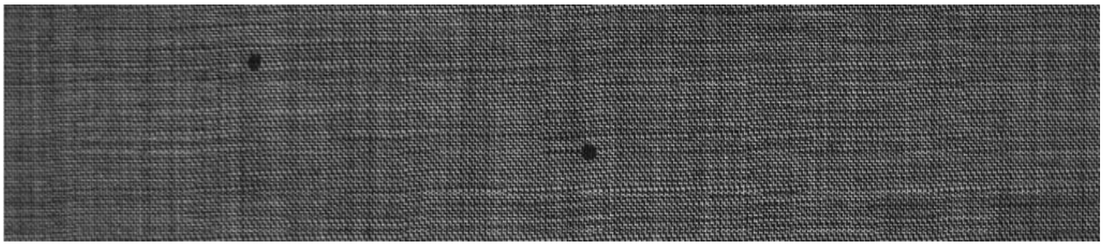

Figure 3.20 Original image

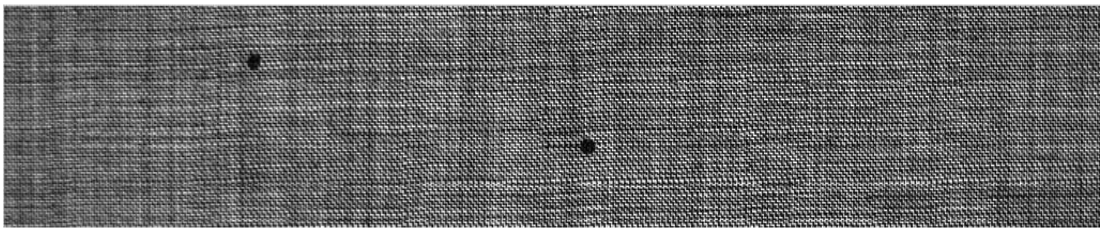

Figure 3.21 Corrected image

2- After the image given in Figure 3.21 has been subjected to Gabor Filter (erosion) process, filter of back plan is obtained. One of the most important stage in the usage of Gabor Filter is optimization of parameter. Parameters may be needed to redetermine by depending on types of fiber. In Figure 3.22 the result of Gabor Filter has been given.

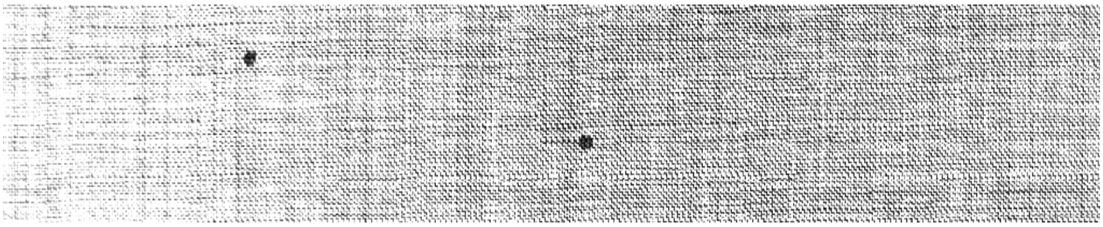

Figure 3.22 The result of Gabor Filter

3- The result obtained from Gabor Filter directly may be impossible. Under the circumstances, errosion process with other filters goes on. In this study, Entropy Filter, Wiener Filter, Fspecial/disk Filter have been used successively. In figure 3.23 the result of Entropy Filter has been given; In figure 3.24 the result of Wiener Filter, In figure 3.25 the result of Fspecial/disk Filter.

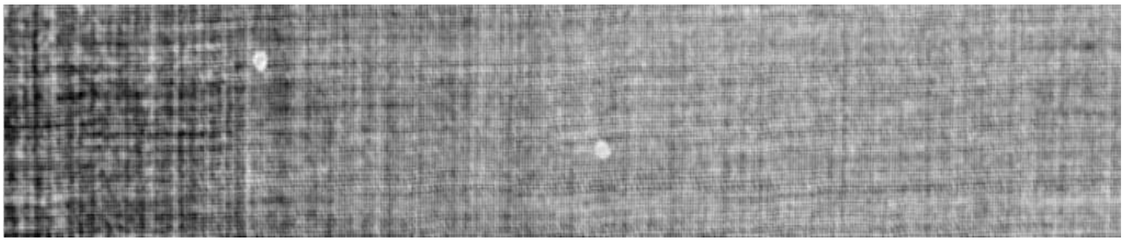

Figure 3.23 The result of Entropy Filter

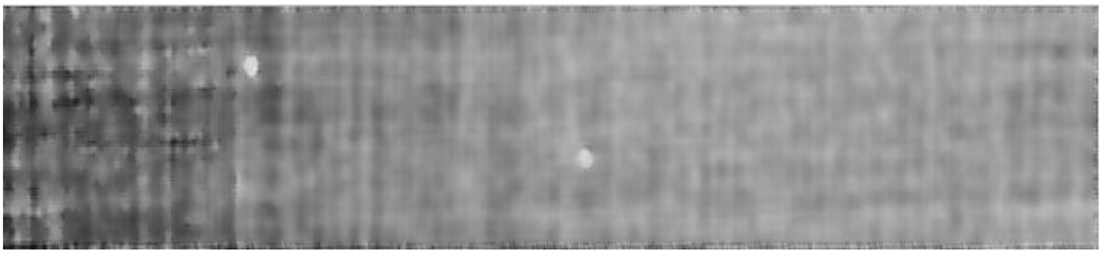

Figure 3.24 The result of Wiener Filter

Figure 3.25 The result of Fspecial/disk Filter.(after process of blur)

4- The image is converted from gray scale to binary image later. In this conversion stage, all pixel values except white ones is taken as black. Therefore, pixel group remaining show errors. Small white pixel group (noisy) without error is cleaned by being passed from a new filter. In figure 3.26 the image obtained after process has been given. In Figure 3.27. mark of errors on the original images has been processed.

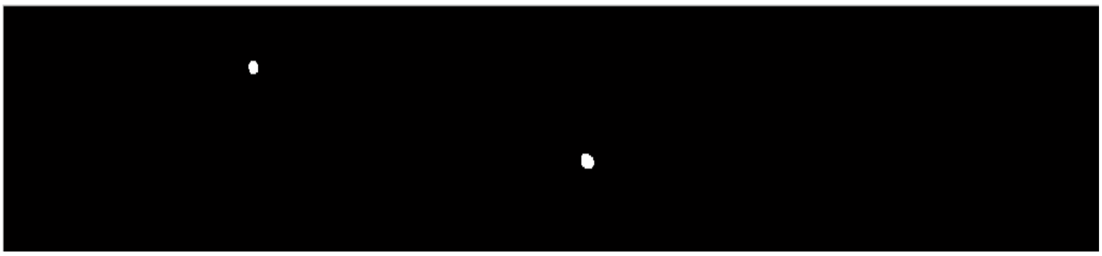

Figure 3.26 The result of Threshold process

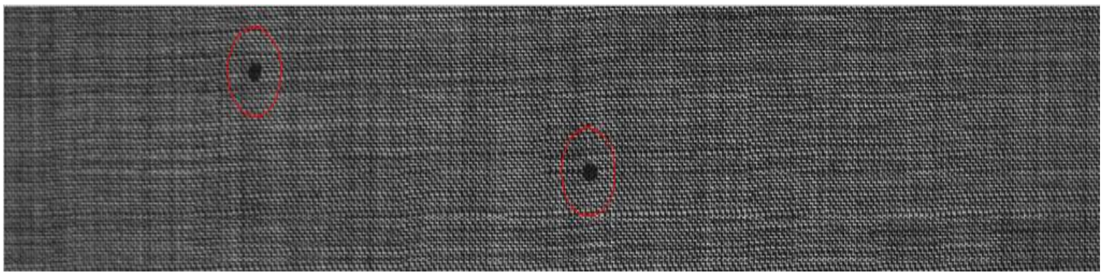

Figure 3.27 Mark of errors on the original images

5- Output programme indicating coordinates and fields of error has been given in Table 3.6.

Table 3.6 Output programme indicating coordinates of error and field of image

Number of Faults	X – Axis (Pixel)	Y – Axis (Pixel)	Area (Pixel)
1.	466,34	74,91	242
2.	1088,22	188,22	372

Elapsed Time: 2.709471seconds

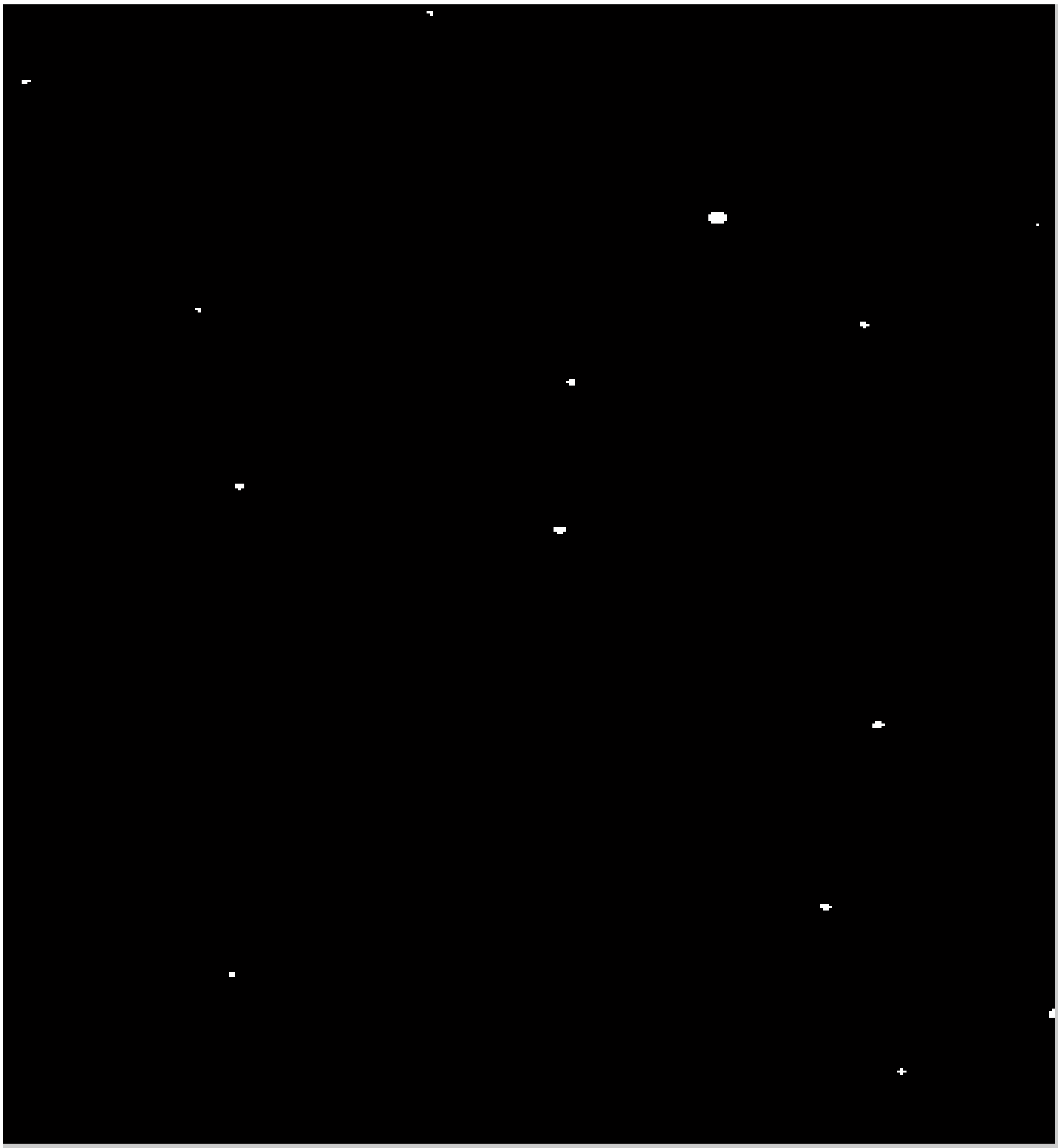

Figure 3.28 The result of image process of united ten several pictures

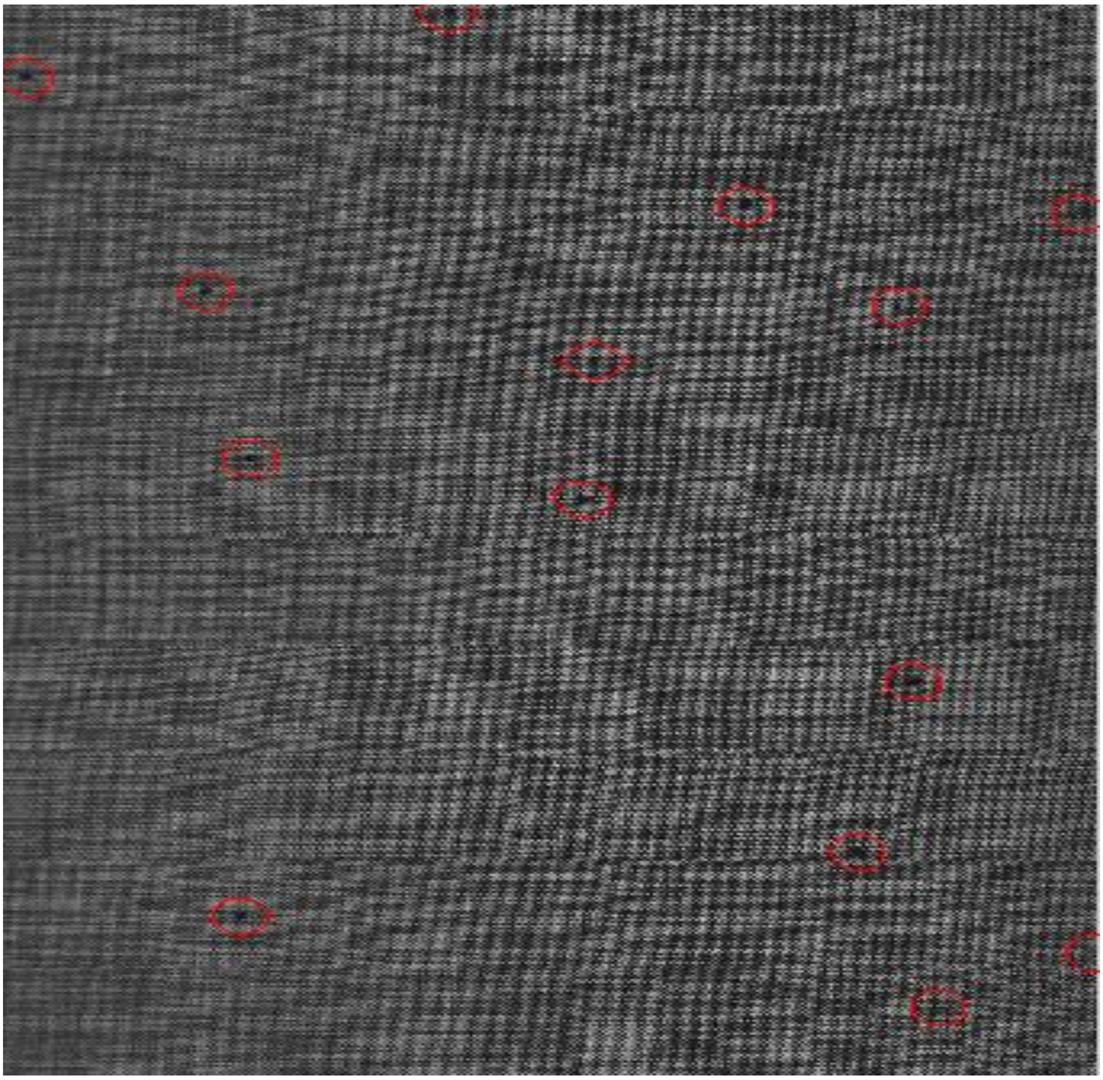

Figure 3.29 Mark of errors on the original images

Table 3.7 Output programme indicating coordinates of error and field of image

Number of Faults	X – Axis (Pixel)	Y – Axis (Pixel)	Area (Pixel)
1.	52,07	209,65	160
2.	385,22	808,27	133
3.	450,20	2556,07	133
4.	466,48	1274,91	216
5.	836,61	28,55	144
6.	1088,57	1388,64	319
7.	1111,73	1001,81	244
8.	1393,85	568,64	936
9.	1603,15	2378,41	317
10.	1677,37	848,90	209
11.	1705,66	1900,73	314
12.	1751,09	2811,87	196
13.	2014,64	588,25	62
14.	2042,51	2659,97	243

Elapsed Time: 27.446141seconds

3.4 Wigner Distributions Operations

According to table, Wigner operation method has been preferred in the determination of small errors, because its accuracy feature is moderate, computational time is excellent and finally algorithm density is complex. The process steps of this method has been shown in figure 3.30.

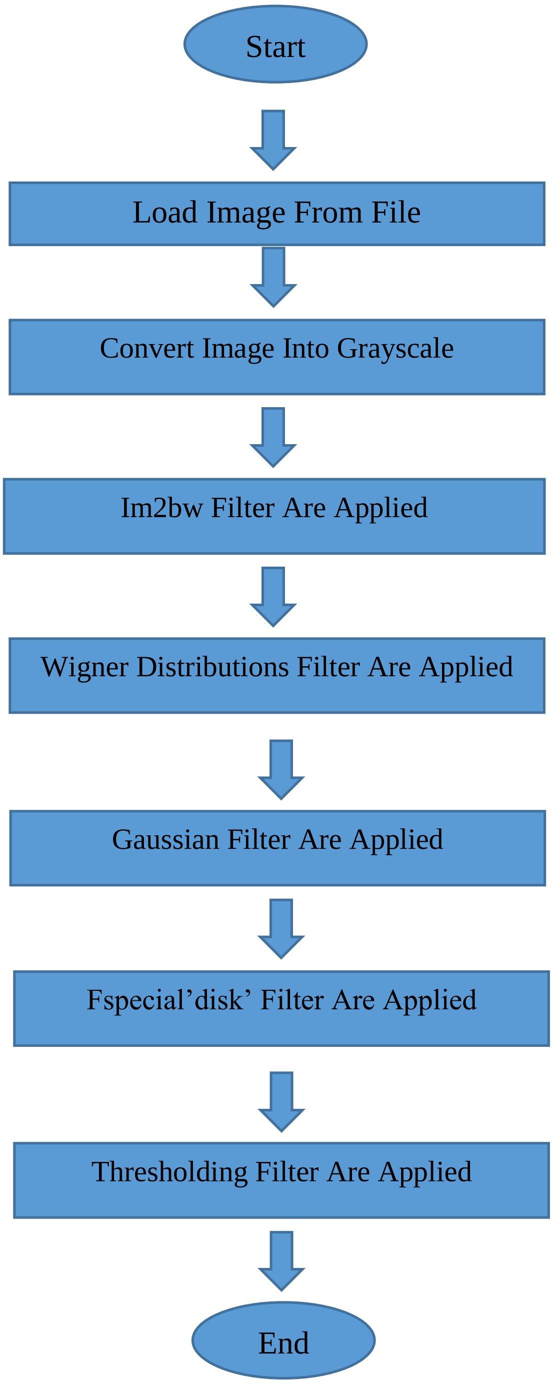

Figure 3.30 Wigner Distribution Filter Operation of flow chart

1- Firstly, the process of conversion to black-white format has been applied to image. In Figure 3.31, black-white format of image has been given.

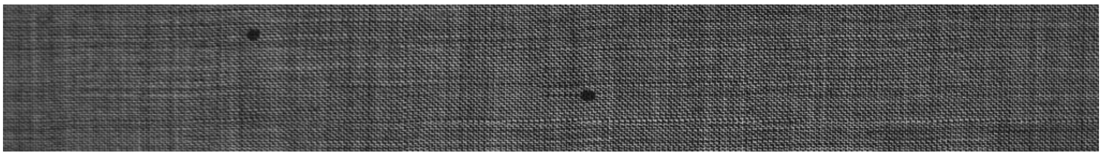

Figure 3.31 The result of black-white format

2- The image is converted from gray scale to binary image later. In Figure 3.32, image has been obtained after this process.

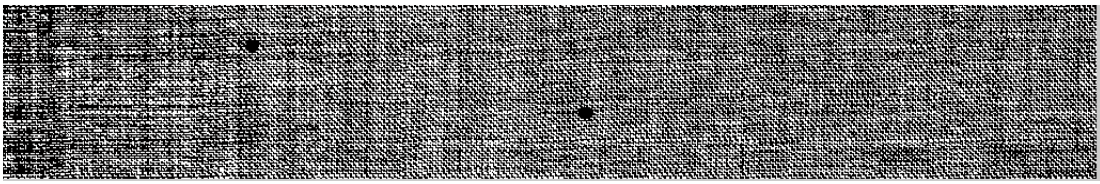

Figure 3.32 The result of im2bw filter

3- Wigner Distributions filter implemented in the next step, the error on the fabric was provided to be more pronounced by covering some black areas on the image.

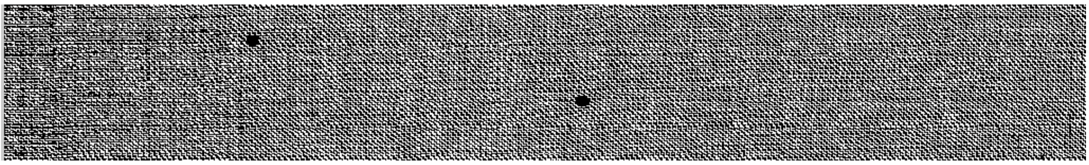

Figure 3.33 The result of Wigner Distributions filter

5- By having subjected to twice gaussian filter process the image in Figure 3.33 enables errors more available. In Figure 3.34 the result of gaussian filter has been given.

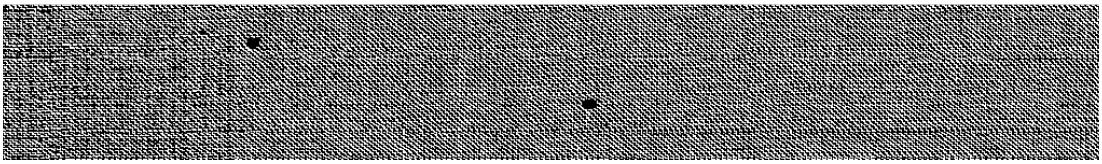

Figure 3.34 The result of gaussian filter

6- Because homogenizing value of pixel makes point more available, disk-shaped blur process has been applied to Figure 3.34. In Figure 3.35, the end of application is given.

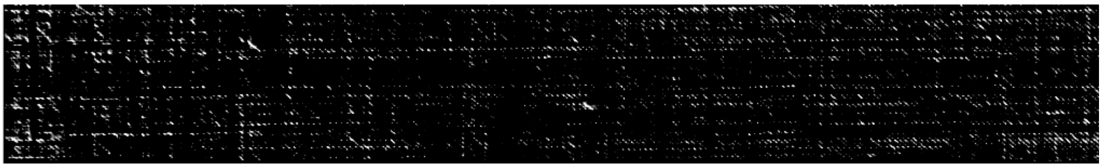

Figure 3.35 The end of disk-shaped blur of image

7- In this conversion stage, all pixel values except white ones is taken as black. Therefore, pixel group remaining show errors. Small white pixel group (noisy) without error is cleaned by being passed from a new filter. In figure 3.36 the image obtained after process has been given. In Figure 3.37 mark of errors on the original images has been processed.

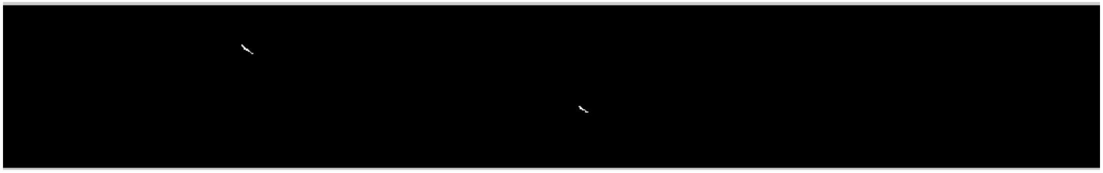

Figure 3.36 The result of Threshold process

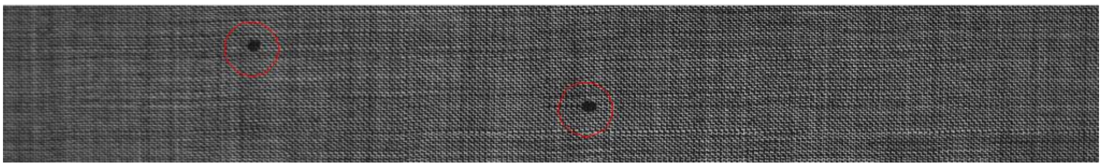

Figure 3.37 Mark of errors on the original images

8- Output programme indicating coordinates and fields of error has been given in Table 3.8.

Table 3.8 Output programme indicating coordinates of error and field of image.

Number of Faults	X – Axis (Pixel)	Y – Axis (Pixel)	Area (Pixel)
1.	459,66	77,66	9
2.	1084,00	191,83	30

Elapsed Time: 4.772531 seconds.

Figure 3.38 The result of image process of united ten several pictures.

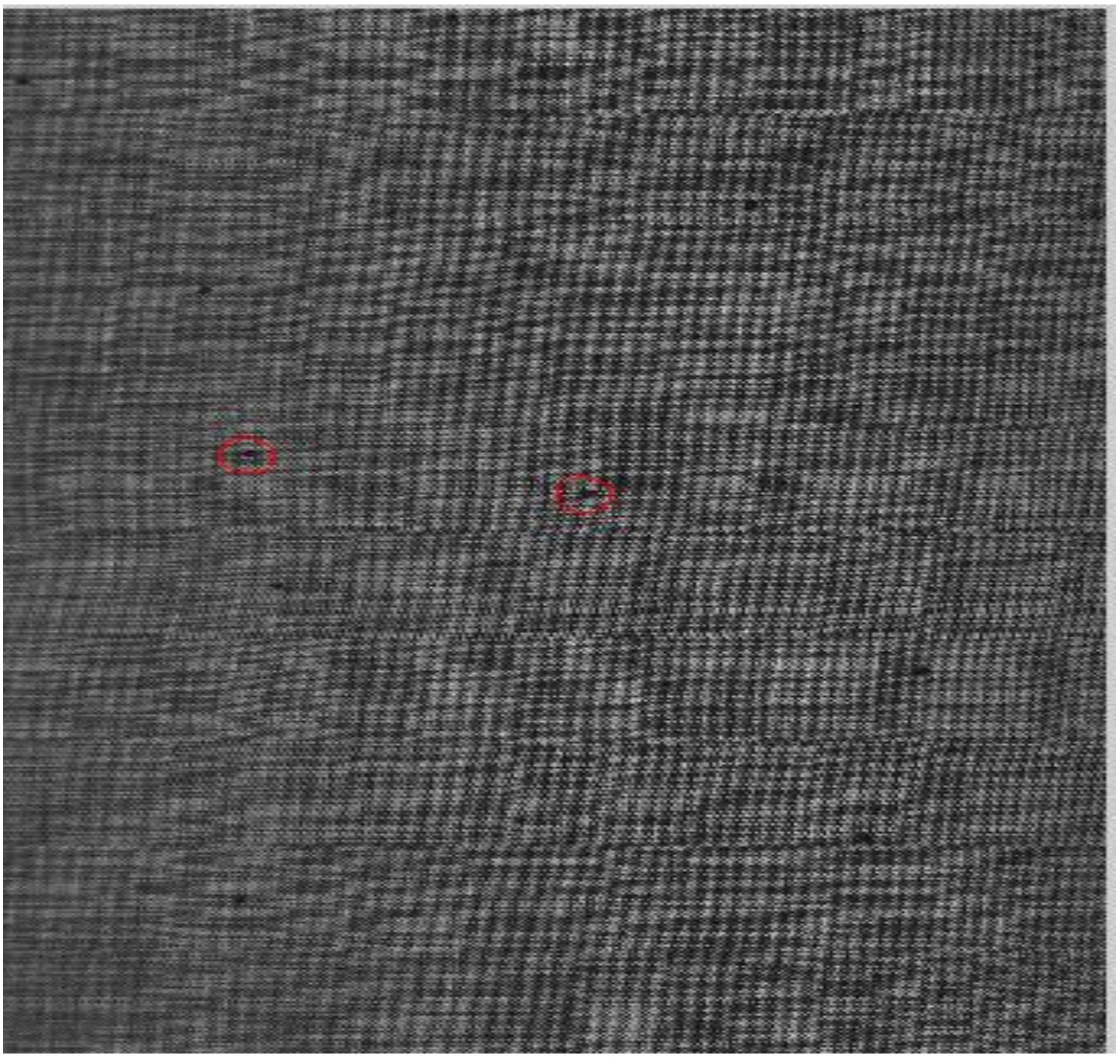

Figure 3.39 Mark of errors on the original images.

Table 3.9 Output programme indicating coordinates of error and field of image.

Number of Faults	X – Axis (Pixel)	Y – Axis (Pixel)	Area (Pixel)
1.	463,30	1281,35	73
2.	1085,23	1393,23	64

Elapsed Time: 34.399030 seconds.

CHAPTER 4

CONCLUSION

Quality inspection of textile fabric products is an important problem for fabric manufacturers. This thesis presents determination of a suitable image processing method for a vision-based neps cleaning robotic system for woolen fabrics. Typical fabric is 165 cm wide and robotic system is intended to clean 30 neps/minutes. At present, the neps cleaning process is manually performed by experts. However, they cannot detect more than 60% of the overall defects for the fabric if cleaning speed is faster than 10 neps/minutes. In this study, a PC-based real-time nesp cleaning system is proposed with benefits of low cost.

In recent times, optical devices are being incorporated into mechatronic systems, and many machine-vision-related technologies have contributed to integration of optical technology with mechatronics in order to have engineering systems equipped with intelligence. Applying machine vision techniques in industry has received a great deal of attention, and many systems for a variety of applications have been successfully implemented in the last two decades. Most of the efforts in vision research were devoted to making individual modules more efficient in performing a specific task. The development of a flexible, efficient, reliable, and integrated real-time vision system for industrial applications is an essential issue in current and future research. The inspection of fabric quality is also an important area in the textile industry. Like other inspection processes, it has depended on workers' experience until now. However, the high cost of human visual inspection has led to the development of online vision-based integrated systems capable of performing inspection tasks [127]–[128]. Fabric defects inspection is one of the main steps of fabric quality control and management. Fabric defects detection with human vision causes extensive hard work, low speed, and more false detecting rate, detecting loss and inconvenience of data management, etc. Automatic fabric defects detection is fast and effective way to i dentify and locate defects accurately while maximizing the throughput. Nowadays, not only computer image processing technologies are used, but also some algorithms are proposed for image processing. These methods were explained in details in chapter 2. Each of these inspection method has its own limitations and defect detection is limited to a certain range of defects. Fabric defect detection is still a topic of considerable research and researchers have proposed different algorithm to reduce the cost, and improve the throughput and range of defects that can be detected. In this study four image process methods were determined as suitable candidate for automatic neps type of defect detection for woolen fabrics. These are;

Morphological operation method: The term morphology refers to the description of the properties of shape and structure of any objects. In the context of computer vision, this term refers to the description of the properties of shapes of areas on the image. In the first place mathematical morphology is used to extract some properties of the image, useful for its presentation and descriptions. Also morphological method is used in the preliminary and final image processing. It is clear that the shape can be arbitrary, as long as it can be represented as a binary image of a given size. The result of morphological operation depends on the size and configuration of the original image and the structural entity. One major advantage of the morphological process is its simplicity.

Gabor Filter method: Gabor Filter is extensively used for segment, recognition, edge extraction and surface inspection of texture image. Fabric surface is a typical texture structure and has properties of periodicity, direction and uniformity. Fabric defect breaks texture uniformity on frequency and direction. So the different response of Gabor Filter may describe the fabric defects automatically. However, determination of filter parameters to get the best result requires experiences. The experimental results show that the efficiency of the filter method for inspecting fabric defects. Additionally, Gabor Filters have been particularly successful in many computer vision and image processing applications. In biometrics, for example, this method is very effective for iris recognition, Gabor features are among the top performers in face recognition and fingerprint matching.

Adaptive Threshold Method: Thresholding is one of the most important process of image process. Especially, it is used to determine close and distinct areas of objects in image. It includes the arrangement of the image separated by pixels until binary structured image. Simply, thresholding process is the process which pixel values on the image are thrown out according to a determined value and other value, values are placed instead of that. Utilization of gray level thresholding provide to determine high contrast faults. This event of a fault reasons the signal level to increase or decrease locally; the presence of a hill or hole after that demonstrate a defect. That defect is determined when the signal crosses a result threshold. This method is used to fabric fault determination on moving textile web.

Wigner distribution operation: The Wigner distribution function is Fourier-like however has been shown to provide better conjoint resolution than Gabor or Gaussians for conjoint spatial and spatial-frequency image representation. The fabric fault detection techniques applying optimal FIR filtration systems and Wigner distributions have been indicated to be very effective to determine a types of fabric faults. But, the utility for unsupervised web supervision, within simultaneously determination of faults from a large number of classes, is yet to be indicated. This algorithm is beneficial as soon as executed for on-line fabric fault detection however its computation time is prohibitive. Nevertheless its utility for unsupervised fabric inspection, at the same time percepting blemishes a lot of classes, is actually but to be shown. The major disadvantage in this method may be the existence of interference terms between the different aspects of the image.

The above image process methods were tested to compare their effectiveness and speeds by using the images of sample woolen fabrics. Therefore, software programs were prepared for each method by MATLAB and C++ compiler. The results show that Morphological Operation method detects the neps of fabrics in the range of 80-90% success. The computational time, of course, depend on the power of the computer. Therefore, computational time for morphological operation method is accepted as 1 unit. The test results of the Gabor Filter method is quite different that of Morphological Operation. This method again detects the neps fairly good (80-85%) however the computational time is approximately 12 time longer than Morphological Operation method. Adaptive Threshold method is also successfully detects the neps. The effectiveness of the method changes between 75-80%, but the computational time is approximately 6 time longer than Morphological Operation method. Wigner

Distribution Operation method produces very poor results. The method detects the neps with a success in the range of 20-25%. The average computational time is approximately 15 times longer than that of Morphological Operation method.

As a result, Morphological Operation method is chosen as the most appropriate method to determine the neps type defects. Therefore, it was used as a basic image processing method while the other were used as auxiliary methods.

In the thesis image processing methods were examined to determine the most suitable method for on line image processing and neps cleaning purpose for woollen fabrics. Most of the image processing studies are related with the inspection and classification of fabric faults, however, this study aims on-line image processing to determine neps and their locations to be used for neps cleaning process by a robotic machine. As a consequence, the most suitable image process method was determined by systematically analyzing and experimentally testing the effectiveness and computational time of each method. The selected method was applied to a computer vision neps cleaning robot for on line image processing and neps cleaning purpose.

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