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FABRIC DEFECT DETECTION IN FREQUENCY DOMAIN USING FOURIER ANALYSIS

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Nuri Gökay Titrek
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Nuri Gökay Titrek

APPROVED BY:

Assoc. Prof. M. Taner Eskil (Thesis Supervisor)	Işık University	__________________
Assoc. Prof. Olcay Taner Yıldız	Işık University	__________________
Asst. Prof. Mehmet Önal	Işık University	__________________

APPROVAL DATE: ..../..../....

FABRIC DEFECT DETECTION IN FREQUENCY DOMAIN USING FOURIER ANALYSIS

Abstract

An overwhelming majority of image processing based defect detection approaches rely on machine learning methods to train a model for comparison of test examples. This requires a training phase for each item to be learned and costly computations to tune model parameters. The fabric of textile always has repeating patterns that lends itself to automating the training phase by extracting a template. We avoid computationally costly machine learning methods by simple comparison of the fabric template with test examples in the frequency domain. In this thesis we show that it is possible to do online and fully automated defect detection of textile products in real time. We propose a method that leverages Fourier transform of textile images and present results on a data set that is collected in the scope of this research.

Keywords: Textile Defect Detection, Image Processing, Fourier Transform, Online

DOKUMA ÜZERİNDEKİ HATALARI FREKANS BÖLGESİNDE FOURIER ANALİZİ İLE BULMA

Özet

Görüntü işleme tabanlı hata tespit yöntemlerinin çoğunluğu makina öğrenmesine dayalı, önceden modellenmiş ve test örnekleri ile karşılaştırmaya dayalı sistemlerdir. Bu eğitim işlemi her bir malzeme için yapılarak sistemin öğrenmesi sağlanmalıdır ki bu işlemin maliyeti yüksektir. Dokuma üzerindeki desenler kendisini tekrar ettiği için eğitim aşaması yerine, taslak çıkartarak otomatikleşmesini sağlayabiliyoruz. Makina öğrenmesi gibi maliyetli işlemleri kullanmak yerine, elde ettiğimiz taslak ile test örneklerini, frekans alanında basit şekilde karşılaştırabiliyoruz. Bu tez çalışmasında, bu yöntemin online ve tamamen otomatize edilmiş gerçek zamanlı bir hata tespit sistemi olacağını göstereceğiz. Önerdiğimiz metod, Fourier dönüşümü kullanılarak geliştirilmiş ve bu çalışma süresince toplamış olduğumuz dokuma görüntülerinden oluşan veri setine uygulanarak, elde edilen sonuçlar sunulmuştur.

Anahtar kelimeler: Dokuma Hata Tespiti, Görüntü İşleme, Fourier Dönüşümü, Online

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To my dad…

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List of Abbreviations

FT	**F**ourier **T**ransfrom
IFT	**I**nverse **F**ourier **T**ransfrom
DFT	**D**iscrete **F**ourier **T**ransfrom
FFT	**F**ast **F**ourier **T**ransfrom
IFFT	**I**nverse **F**ast **F**ourier **T**ransfrom
NCC	**N**ormalized **C**ross-**C**orrelation
SE	**S**tructuring **E**lement

Chapter 1

Introduction

1.1 Introduction

Variety of products and requirement of faster production is making quality control difficult in textile sector. Meanwhile customers are becoming more considerate in the quality of products. Thus, importance of quality control is undeniable. Nowadays, both graphical and core processing capabilities are highly improved which provide great opportunity to automatizing quality control management. However, textile defect detection is still an unsolved problem and the technologies behind it has to be improved.

Our approach is finding defects without need of machine learning and finding features, which will be explained further in the following paragraphs. The rationale behind our approach is that wide variety of textile designs make machine learning and finding features extremely expensive.

An important challenge in research of textile defect detection is the lack of a benchmark data set for comparison of proposed approaches. In this study we also collect a data set for various types of defects. This data set will be used in our research and it will be made available to future researchers of the field.

1.2 Fabric Inspection

In traditional inspection, quality control machines are manned by quality specialists. Standard textile quality control machines have approximately 300-400 centimeters lines which need at least 2 employees to watch (Figure 1.1). Line movement speed is stabilized to 8-20 meters per minute [1]. When an employee notices a defect on the moving fabric, he stops the engine that moves the fabric roll, records the defect and its location, and starts the motor again. Staring at the machine for a long period of time causes eyestrain and day-dreaming which results defects such as do-overs or missings, etc. Inefficiencies in quality control departments force companies to create sample tests instead of checking the whole unit.

An efficient quality control department has to examine the product in two stages:

1. Raw Product Control: This is the checkpoint when the absolute product is just out of the fabric machine without any process applied. In here, defects are determined which are caused by the weaving machine.
2. Semi Product Control: Quality control is also critical for processed products. These processes include coloring, yarn, trimming, crushing, touching.

It would be the best way to divide difficulties of defect detection in two categories, products based and image processing based:

1. Product Based Difficulties
   (a) Design varieties, new patterns or specifically designed fabrics for customers are increasing number of products. The differences of each pattern or texture of the fabric generates even more design varieties (Figure 1.2).
      i. Printed fabric

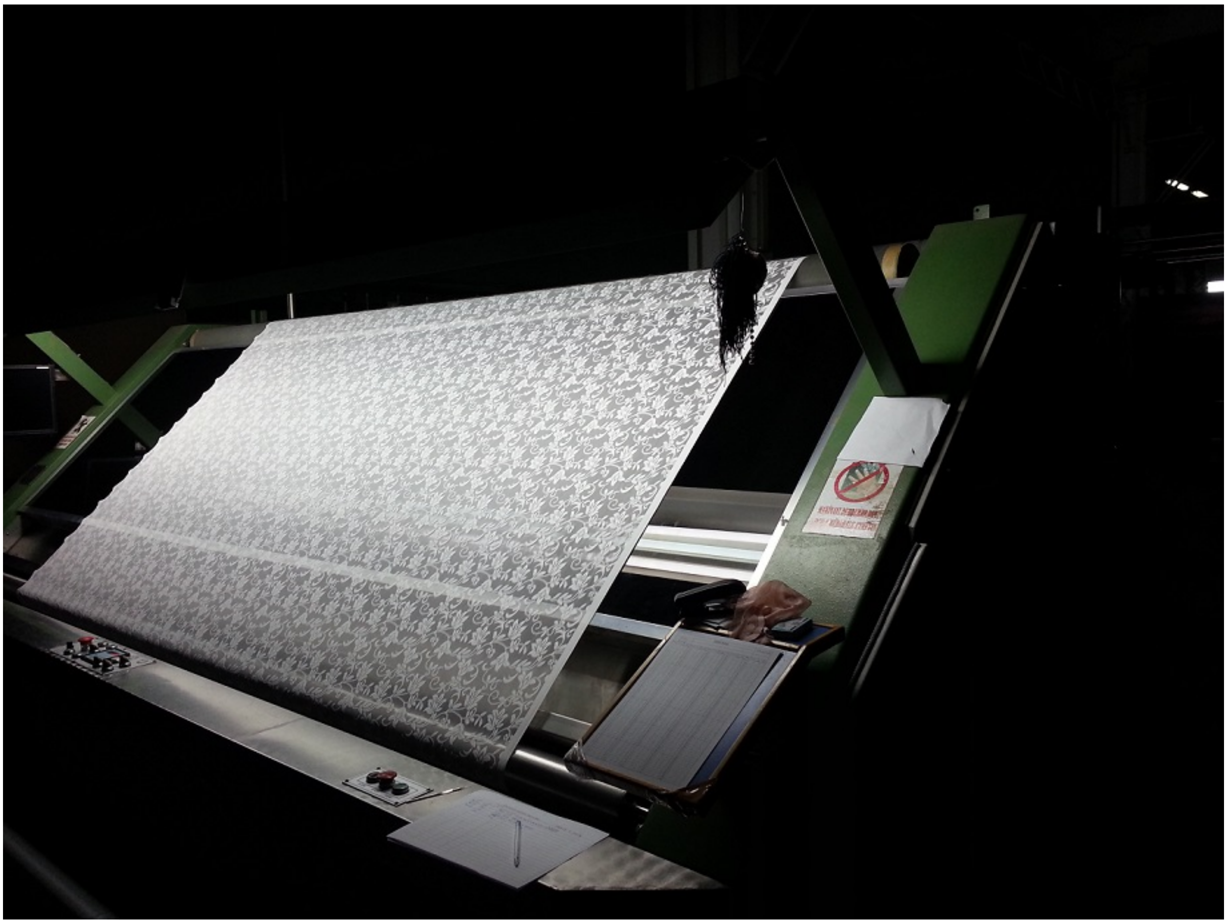


Figure 1.1: A typical textile quality control machine

        ii. Solid color fabric

        iii. Special designs etc.

    (b) Thinness and transparency of the fabric make detecting defects harder.

    (c) Error varieties (Figure 1.3).

        i. Design

        ii. Color

        iii. Tear

        iv. Warp breakage

        v. Weft insertion etc.

2. Image Processing Based Difficulties

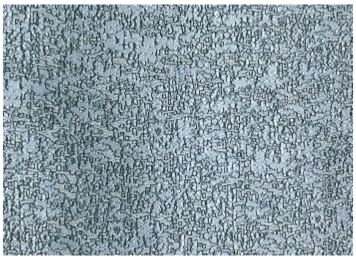
    (a) Rotation

(b) Dimension

(c) Lighting

(d) Scale

(a) Printed



(b) Special design

(c) Special design

(d) Solid color

Figure 1.2: Design varieties

1.3 Literature Review

There are quite a few studies which are developed for the purpose of determination of fabric defects. We will review related studies in the next paragraphs.

Kumar A. [1] prepared a survey that compares fabric defect detection techniques using image processing methods. These techniques were classified into three categories; statistical, spectral and model-based. The performance achieved with these approaches are highly variable. Fusion of these features or classification algorithms produce better results than one by one usage of these techniques, and is suggested for future research.

Tsai and Huang [2] proposed a fabric defect detection approach using Fourier transform. This approach detects defects in randomly textured surfaces such as sandpaper, castings, leather etc. It does not need to find local defect, hence it is based on a global image reconstruction scheme using the Fourier transform. Defected area is found by removing repetitive texture patterns using small circular samples from the center of the Fourier spectrum image, and then detecting the anomaly out of the restored image.

Lambert and Bock [3], suggest that multiresolution wavelet methods should be used to find texture defects. Also the detection must be done in multiscale format due to the characteristic of the texture. The features have been found and classified by calculating wavelet packet transform coefficients. The outcome of the tests, which were done by fast dyadic wavelet transform and à trous wavelet transform, has been positive.

Yean Yin et al. [4] aimed to detect failures such as oil stain and holes. Wavelets are used for attenuating the background of the pattern in fabric thus the flaws remain. The main difference between defects is that "hole" type has more whites while the "oil stain" type has deepest black. The histograms of these images have features to distinguish the types of defects. Afterwards by using the two layer back-propagation neural network, the defects are classified as two main groups that are oil stain and hole.

Texture type can be classified either as structural or statistical [5]. In their study, Tsai and Hsieh [6] proposed to detects defects for a specific structural texture, called directional texture. Fourier transform is used for characterizing the pattern. The line patterns of any directional textures found by Hough transform in Fourier domain image. Available lines and neighbors are eliminated by setting them to zero. After cleaning directional patterns, only local anomalies remain on gray-level image when image is reconstructed by inverse Fourier transform. After that, threshold is applied on gray-level image to find defects. The features that are obtained from system are compared to Gabor-filter's features.

Chetverikov and Hanbury [7], propose two fundamental structural properties, regularity (periodicity) and local orientation (anisotropy). The first one looks for regions of abruptly falling regularity. The second one considers the dominant orientation. Both methods are applied on two different databases and they are compared with each other. These methods provide reasonable results to detect defects on structural texture. Each method mentioned in this article has its own advantages, therefore combination of them give better results.

In study [8], three-dimensional frequency spectrum is obtained as the output by using Fourier transform. It is difficult to analyze the output. The method of central spatial frequency spectral extracts two diagrams from the output of Fourier transform. There are seven features to extract the types of defects by using these diagrams. The defects are classified as four main groups which are generally used for defect classification.

Kumar and Pang [9] used a Gabor-filter bank occurring from four dimension and orientation. Each one is applied to the image and the results are recorded. Low frequency features of acquired image are used for feature enhancement. An image of all scales in the image pyramid are fused into single image using Bernoulli's rule of combination. Afterwards, threshold is applied on fused image to find defects. It is possible to achieve poor results if filters are not properly adjusted for the defects.

Fourier Transform has a substantial place between image processing techniques. It transforms time domain to frequency domain which converts image to two-dimensional complex function. This gives us an magnitude spectrum and higher values in that spectrum informs us about recurring pattern and its direction. Therefore, magnitude spectrum allows us to catch periodic structure on the image [10–13]. When a defect occurs on the fabric, periodicity will be corrupted so, there will be distinct spots on the spectrum [14]. Peaks on the spectrum can be used as features [15] so that lets us to analyze recurring patterns and defects. Those features are eligible to use determining defects.

Fourier Transform is a very efficient approach for determining defects because fabrics are usually symmetric or have periodic patterns. Nevertheless, the discovered features from FT are basic so they do not gives us kind of the defect or the location of it. Since the Fourier bases can be infinite length, quantifying the contribution from each of the spectral components is an expensive process [16]. FT based systems uses additional systems such as neural networks to get features [10, 13–15, 17]. Indeed, a neural network is not always needed to detect defects by FT. Work of Tsai et al. [2, 6] is based on global image reconstruction scheme using the FT. Zhou et al. [18], developed a textile identifier by using local FT. Firstly, LFT coefficients were calculated and then features were created by using LFH.

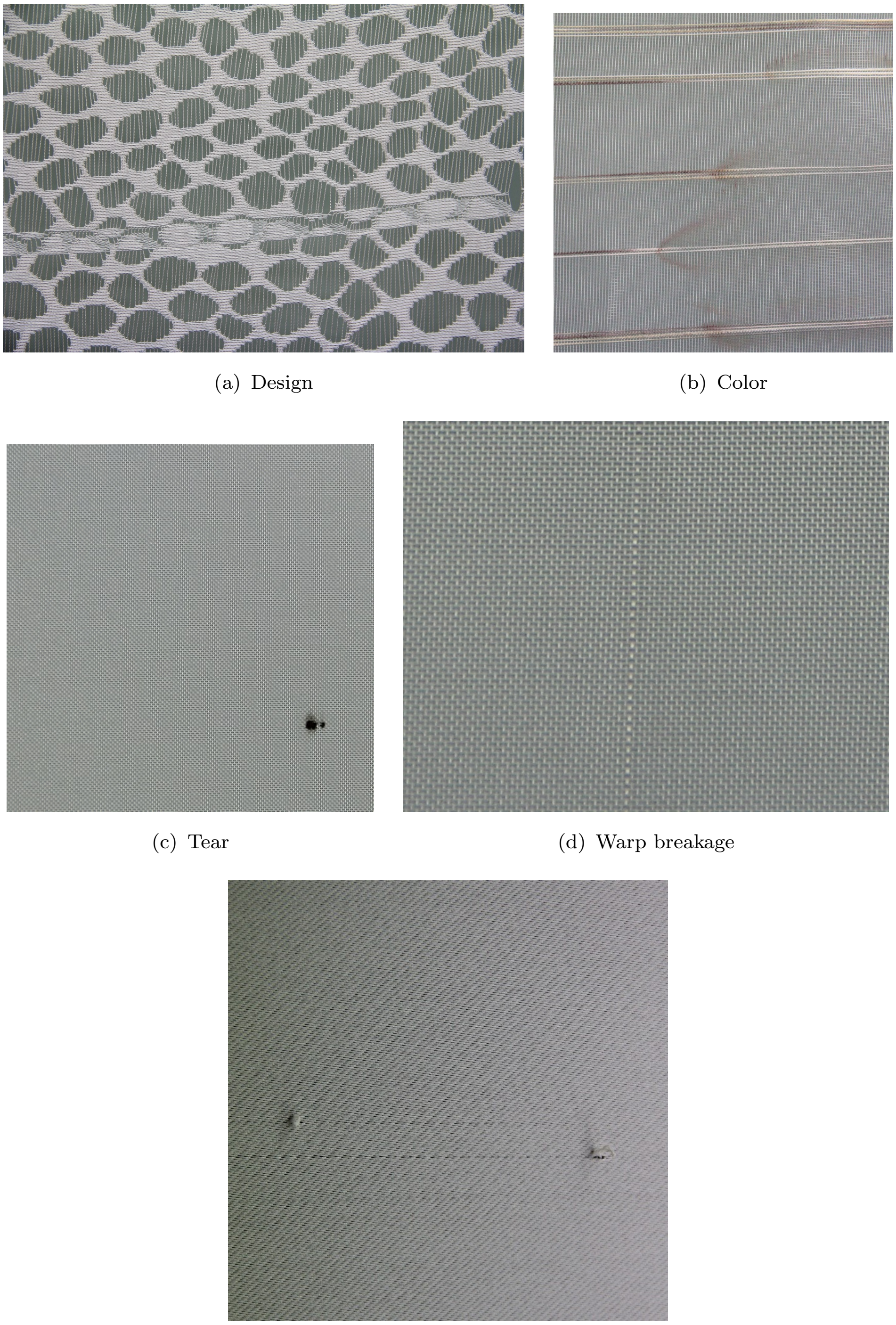
We observe in the literature that there is no common benchmark data set for comparison of multitude of approaches. In review [19], some studies with FT were not tested sufficiently and some others' reliability were unknown despite of their claims as successful [2, 6, 8, 20]. Lack use of a common benchmark database prevents comparability and reliability. A few researchers [5, 7, 18], used common databases such as Brodatz [21] and Tilda [22], and tested their works. Thus, they had the opportunity to compare and analyse each other's studies.

1.4 Research Objectives

Our goal is detecting defects on fabric and categorizing them. We need a certain setup for it. For automation of the quality control, we need a camera which can be integrated to the machine so that we can record and process images. That gives us opportunity to increase the speed of line and as a result, efficiency of production. Besides that, we can prevent employee defects so that quality of the fabric is also improved.

Our approach is not a new image processing method. However, it is a new way of applying existing methods in a sequence and evaluating the output.

We intend to collect a data set consisting of various types of defects. It will be the structure of a reference data set with images of textile for purpose of the evaluation of visual inspection algorithms.



(a) Design

(b) Color

(c) Tear

(d) Warp breakage

(e) Weft insertion

Figure 1.3: Error varieties

Chapter 2

Fabric Defects

2.1 Introduction

In this chapter, we are going to discuss types of fabric defects and their causes. Different types of fabrics can be weaved into fabrics. Woven fabric is made by weft and warp yarns (Figure 2.1). These yarns cross and connect each others creating a pattern. Warp yarns are lined up tightly or side to side depending on the weaving type. Weft yarns cross between these warps and finish the pattern. Woven fabrics are the most commonly produced fabric in industry. In this study, we mostly concentrated on woven fabrics defects.

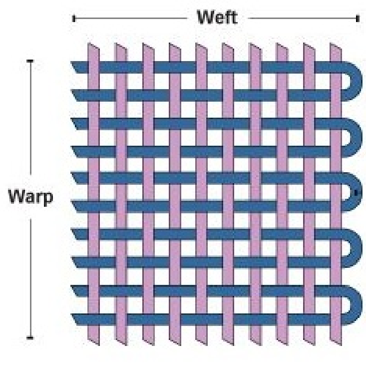


Figure 2.1: Illustration of weft and warp yarns

2.2 Types and Reasons

Defect is a corruption which ruins the appearence of the woven pattern and decreases its quality. Quality changes of yarns can be a reason of defects. The production and storage conditions of yarns affect their quality. Defects on the woven fabric are classified in four groups [23]; warp direction, weft direction, fabric surface and edge defects.

We are going to elaborate the defects that we face in the factory where we create our database for our study.

2.2.1 Warp Direction Defects

The causes of the warp direction defects in fabric are yarns, warping yarn and weaving process. Warp defects proceed in line with longitudinal direction of fabrics. Details of the warp direction defects will be given in the next paragraphs.

2.2.1.1 Broken End

A defect in fabric caused by a warp yarn that was broken during weaving. The number of ends missing may be one or more. Defects can run in short or long distance. (Figure 2.2(a))

2.2.1.2 Tight End

Warp yarn in a woven fabric that was under excessive tension during weaving or shrank more than the normal amount. (Figure 2.2(b))

2.2.1.3 Loose End

If the tension of a warp yarn is low in warping, then this fault appears. The warp tension in warping should be equal and uniform. (Figure 2.2(c))

2.2.1.4 Thick End

Warp yarn that has a diameter too large, too irregular or that contains too much foreign material to make an even, smooth fabric. (Figure 2.2(d))

2.2.1.5 Thin End

The diameter of a yarn is thinner than others. Defect occurs throughout the fabric as line on warp direction. (Figure 2.2(e))

2.2.2 Weft Direction Defects

The reason of the weft direction defects in fabric are preparation of weft and weaving process. Weft defects proceed in line with sidelong direction of fabrics. Details of the weft direction defects will be given in the next paragraphs.

2.2.2.1 Miss Pick

A defect in fabric caused by a missing or out of sequence yarn in weft direction. Defects can be in short or long distance. (Figure 2.3(a))

2.2.2.2 Broken Pick

Weft yarn is broken in the weaving of a fabric appears as a defect. The main cause of weft breaks are rough surface of shuttle, shuttle box, rough or incorrect placement of shuttle eye, loose fitting of pirn in the shuttle, incorrect alignment of pirn with shuttle eye and weak yarn strength. (Figure 2.3(b))

2.2.2.3 Weft Bar

Weft direction bands can be easily distinguished from the rest of the portion of the fabric. The bars may be restricted for a particular length of fabric or may repeat at fixed intervals. The main cause of weft bars are the periodic medium to long term irregularity in the weft yarn, count difference in weft, excessive tension in the weft feed package, variability in pick density, difference in blend composition or in the cottons used. (Figure 2.3(c))

2.2.2.4 Tight Weft

A yarn or parts of yarn are tighter than the others in weft direction. Mistaken tensions are the main reason of tight weft yarn defects. (Figure 2.3(d))

2.2.2.5 Slough Off

Thick bunches of yarn are woven into the fabric in the weft direction due to slipping off of coils of yarn from the pirn during weaving. (Figure 2.3(e))

2.2.2.6 Thick And Thin Places

These are similar to weft bar, but unlike weft bars, it repeats at intervals. They are mainly due to irregular let-off and faulty take-up. (Figure 2.3(f))

2.2.3 Fabric Surface Defects

The reason of the surface defects in fabric are weaving process and faults on machine. Details of the surface defects will be given in the next paragraphs.

2.2.3.1 Oil Stain

Oil or other stains are spot defects of oil, rust, grease or other stains found in the fabric. (Figure 2.4(a))

2.2.3.2 Oily End/Weft

Oily End/Weft defects occur because of dirty yarns. (Figure 2.4(b))

2.2.3.3 Local Distortion

A distortion occurs when there is displacement of warp and/or weft yarns from their normal position. (Figure 2.4(c))

2.2.3.4 Gout

Gout is a foreign matter accidently woven into the fabric. (Figure 2.4(d))

2.2.3.5 Hole

Broken needle causes these defects. (Figure 2.4(e))

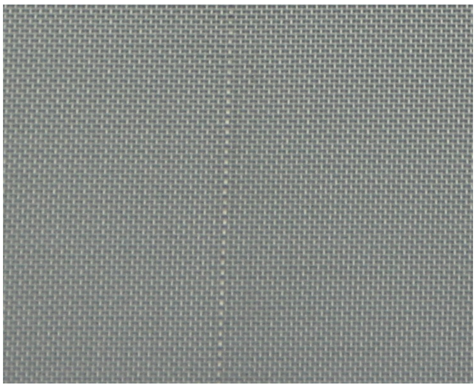
2.2.3.6 Tear

Tear defects are similar with hole defects. Differences of these defects are usually shapes and types of damage. (Figure 2.4(f))

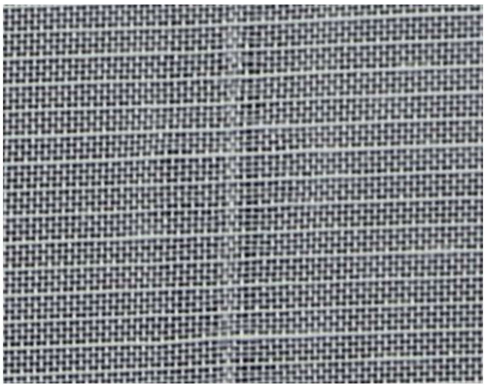
2.2.3.7 Broken Pattern

Broken pattern is the non continuity of a weave, design or pattern. (Figure 2.4(g))

Woven fabrics consist of repetitive patterns. Since defects break these patterns, finding them is our entry point to detect defects. In order to catch, we go through the woven fabric and detect the defected patterns by using FT. The output of the FT represents the image in frequency domain. Repetitive patterns and defected patterns have different frequencies. In our approach which is meticulously explained in Chapter 3, we detect the defects in frequency domain, then transform the Fourier image to spatial domain by using IFT. As result, only defected areas remain on image.



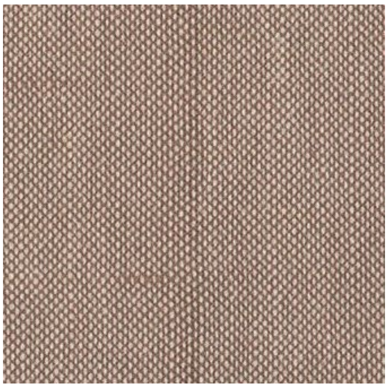
(a) Broken end



(b) Tight end

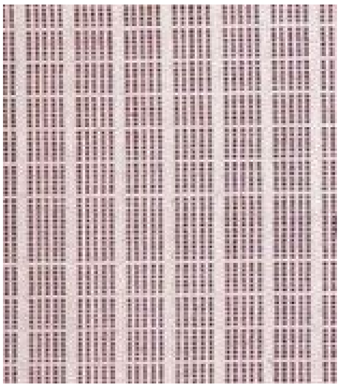
(c) Loose end

(d) Thick end

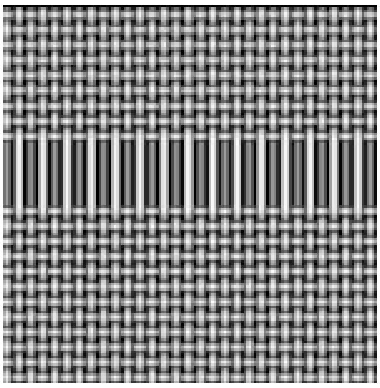


(e) Thin end

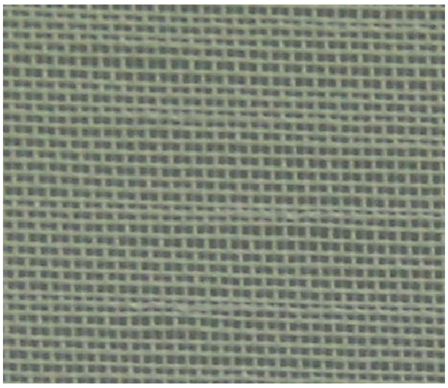
Figure 2.2: Warp direction defects



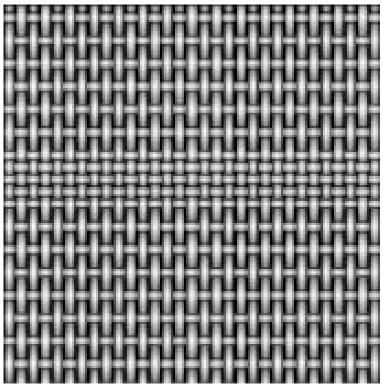
(a) Miss pick



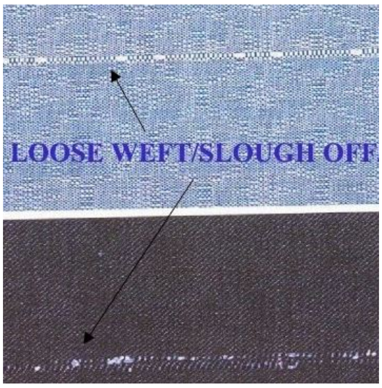
(b) Broken pick



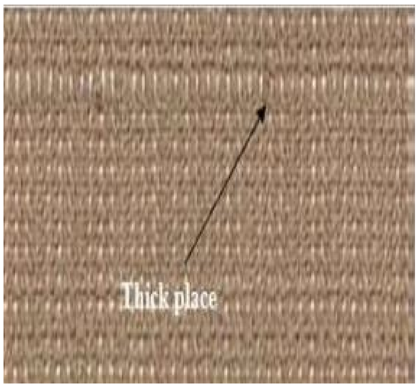
(c) Weft bar



(d) Tight weft

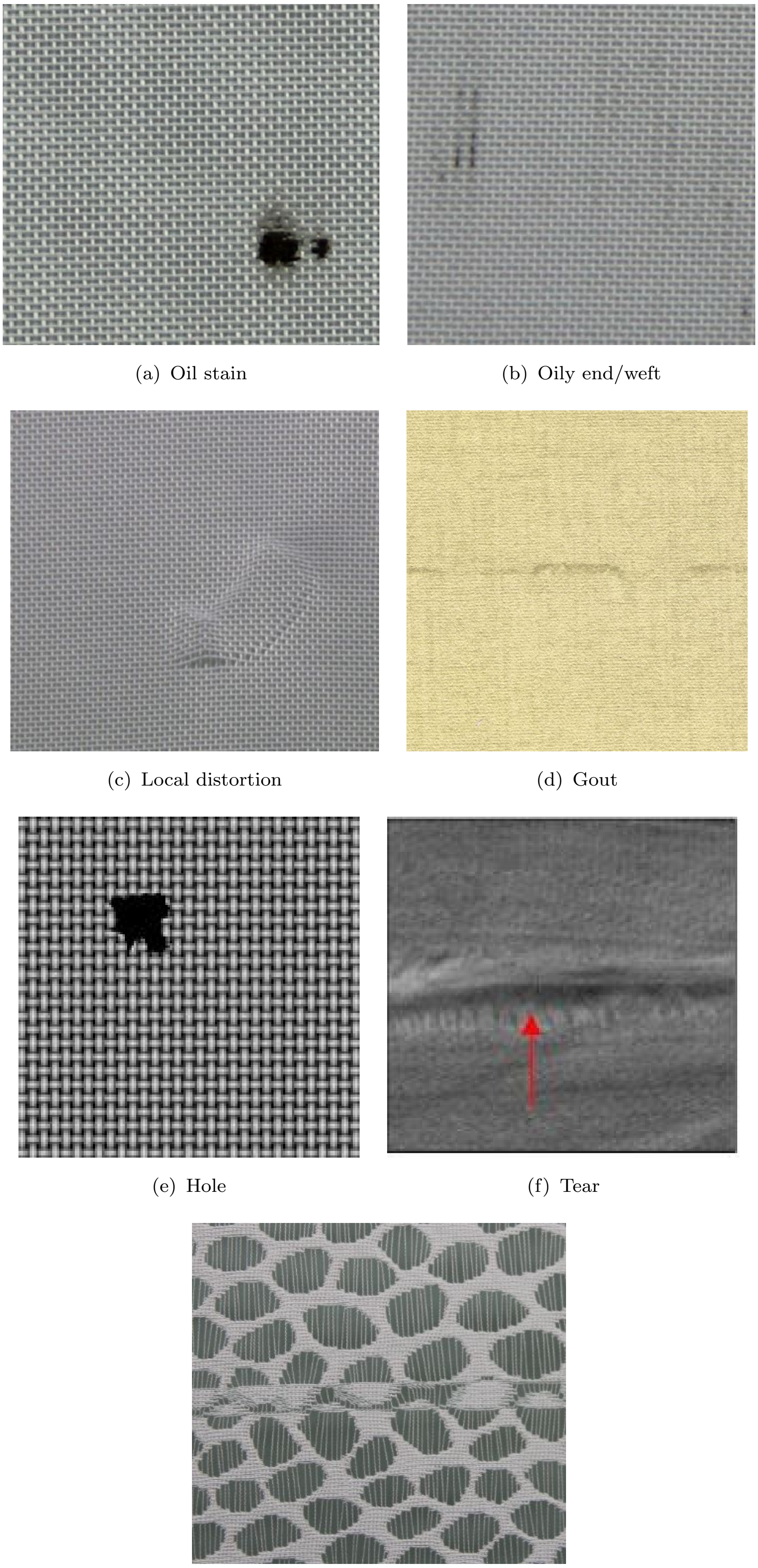


(e) Slough off



(f) Thick and thin places

Figure 2.3: Weft direction defects



(a) Oil stain

(b) Oily end/weft

(c) Local distortion

(d) Gout

(e) Hole

(f) Tear

(g) Broken pattern

Figure 2.4: Fabric surface defects

Chapter 3

Proposed Approach

3.1 Introduction

There are multiple done and ongoing studies for fabric defect detection. If we look into these studies, we see most of them are about filters [9, 16] e.g. gabor filters. Varieties of woven fabrics and defect kinds cause defectiveness for these studies. Thus, we decided a path to build a system which concentrates on corruptions on periodic structures without any defect information. The main method of our study is FT. Besides that, we benefit from cross-correlation and basic image processing methods. Combining many methods together makes the study more powerful and accurate [1] rather than individual usage of them.

By this chapter, we are going to mention about the methods that we used. Then, we are going to explain how we use them and get into the details of our study.

3.2 Description of the Used Algorithms

3.2.1 Fourier Transform

Any signal can be represented by the sum of sine and cosine waves with various amplitudes and frequencies by using the Fourier theorem. FT is the best tool to apply Fourier theorem. FT is important in mathematics, engineering, and the physical sciences. FT uses to analyze different areas such as image processing, sound waves, electromagnetic fields, etc. FT is a reversible, linear transform with many important properties. Equations of FT (3.1) and IFT (3.2) are shown as follows:

$$F(s) = \int_{-\infty}^{\infty} f(x)e^{-2\pi isx}dx \tag{3.1}$$

$$f(x) = \int_{-\infty}^{\infty} f(s)e^{2\pi isx}ds \tag{3.2}$$

Working with the FT on a computer usually involves a form of the transform known as the discrete Fourier transform (DFT). DFTs are useful because they reveal periodicities in input data as well as the relative strengths of any periodic components.

There are different ways to compute the DFT. DFT computation complexity is $O(N^2)$ which is too slow. Fast Fourier transform(FFT) [24] is also a method to compute DFTs with same result as evaluating in DFT definition and the fast computation time is the advantage of this method. FFT computation complexity is $O(N \log N)$. Equations of DFT (3.3) and inverse DFT (3.4) are shown as follows:

$$X_k = \sum_{j=0}^{N-1} x_j e^{\frac{-2\pi ijk}{N}} \tag{3.3}$$

$$x_j = \frac{1}{N} \sum_{j=0}^{N-1} X_k e^{\frac{2\pi ijk}{N}} \tag{3.4}$$

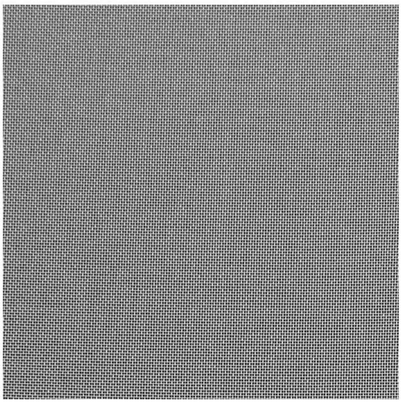
Images are two dimensional so one-dimensional DFT is not proper to apply to them. Computing the FFT of each dimension of the input matrix is equivalent to calculating the two-dimensional DFT. DFT transforms MxN image into another MxN image. Images are transformed to the frequency domain using DFT (3.5) as follows:

$$f(p,q) = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} f(m,n) e^{\frac{-j2\pi pm}{M}} e^{\frac{j2\pi qn}{N}} \tag{3.5}$$

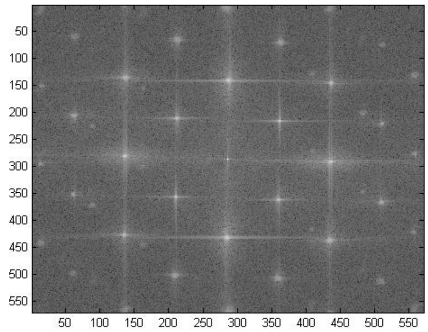
An important property of two-dimensional DFT is its ability to restore the processed image from the frequency domain to its spatial domain. This is usually done using inverse DFT (Figure 3.1(d)). Thus, in a similar way to the previous equation, the Fourier image can be re-transformed to the spatial domain using invserse DFT (3.6) as follows:

$$f(m,n) = \frac{1}{MN} \sum_{p=0}^{M-1} \sum_{q=0}^{N-1} F(p,q) e^{\frac{j2\pi pm}{M}} e^{\frac{j2\pi qn}{N}} \tag{3.6}$$

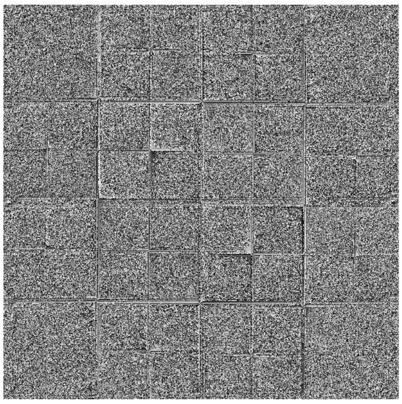
The Fourier transform produces a complex number valued output image which can be displayed with two images, either with magnitude (Figure 3.1(b)) and phase (Figure 3.1(c)). In image processing, It is not necessarily to display more than the magnitude of the Fourier transform as it contains most of the information of geometric structure of the spatial domain image. On the other hand, when we do this process in reverse order after some processing in the frequency domain, it is required to preserve both magnitude and phase of the Fourier Image.



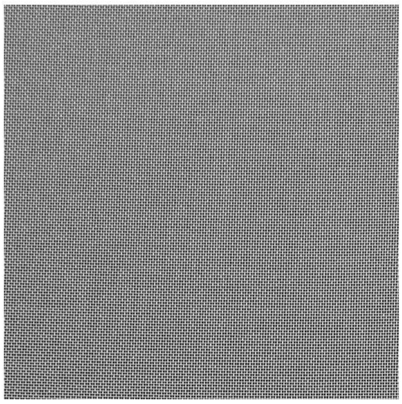
(a) Original grayscale image



(b) Magnitude of Fourier transform



(c) Phase of Fourier transform



(d) Inverse Fourier transform

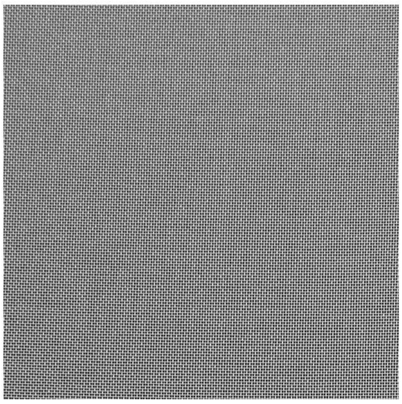
Figure 3.1: Fourier transform

3.2.2 Normalized Cross-Correlation

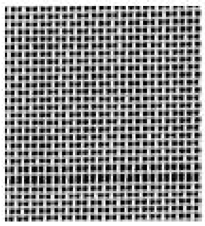
The normalized cross-correlation(NCC) is an accurate measure of similarity between two compared images. It is a basic approach to computes similarity between two images, for feature detection as well as a component of more complicated techniques. The main advantage of the NCC over the ordinary cross-correlation is that is less sensitive to linear changes in the amplitude of illumination in the two compared images. Also, selection of threshold value is easier than ordinary cross-correlation, because of that coefficients of NCC are bounded in the range between -1 and 1. It has applications in pattern recognition, image processing, motion analyzes, etc. Equations of NCC (3.7) is shown as follows:

$$r = \frac{\sum_{(i,j)\epsilon W} I_1(i,j).I_2(x+i,y+j)}{\sqrt{\sum_{i,j} \epsilon W I_1^2(i,j). \sum_{i,j} \epsilon W I_2^2(x+i,y+j)}} \tag{3.7}$$

We choose two different images for evaluation of the NCC method. Source image (Figure 3.2(a)) must be larger than the template image (Figure 3.2(b)) for the normalization to be meaningful. We apply NCC algorithm and display result as surface (Figure 3.3). Peak values on the surface indicate that is best matched areas. Also, peak values of result matrix reveals coordinates of pixel as x and y plane. Starting from these points, when an area is selected according to the image size, we are able to achieve to demonstrate the best correlation between two images (Figure 3.4).



(a) Source image (600x600)



(b) Template image (100x100)

Figure 3.2: Source and template image

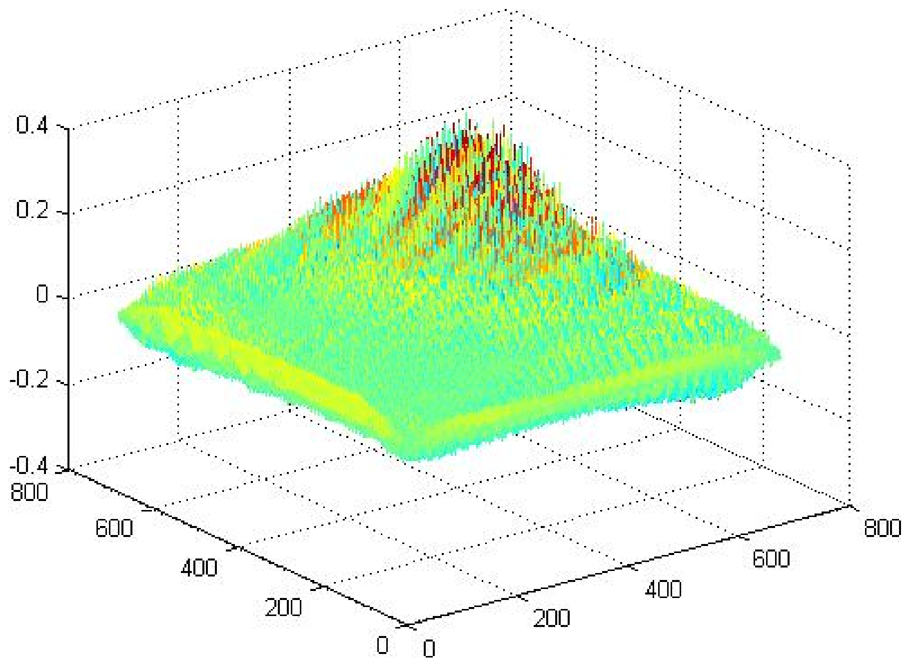


Figure 3.3: NCC result as surface

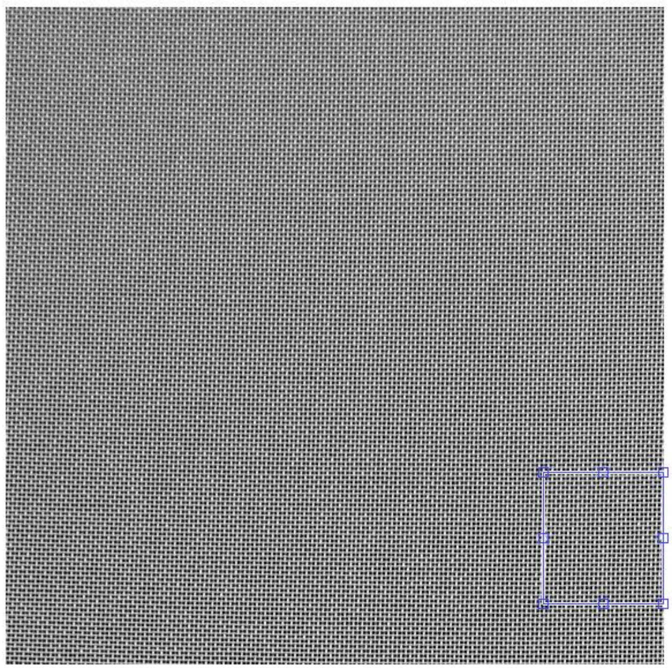
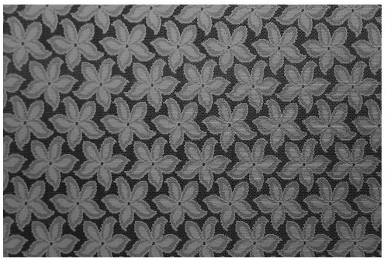


Figure 3.4: Display matched area on source image(Figure 3.2(a))

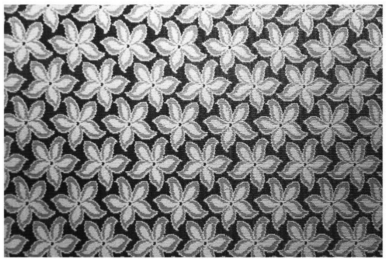
3.2.3 Histogram Equalization

Histogram equalization is a technique for adjusting image intensities to enhance contrast. Zhang and Bresee [25] have utilized histogram equalization in which reassigns grayscale values of pixels to obtain much more uniform grayscale distribution in an image. Equations of histogram equalization(3.8) is shown as follows:

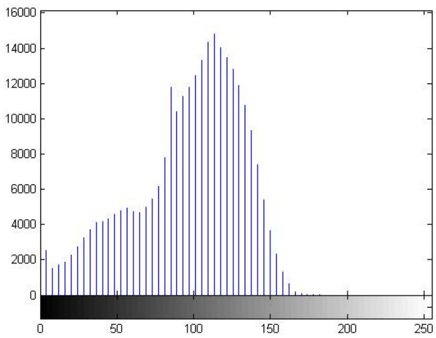
$$\text{L: The number of possible intensity values}$$
$$I_{i,j} = round((L-1)\sum_{n=0}^{i,j}\frac{\text{number of pixels with intensity n}}{\text{total number of pixels}}) \tag{3.8}$$



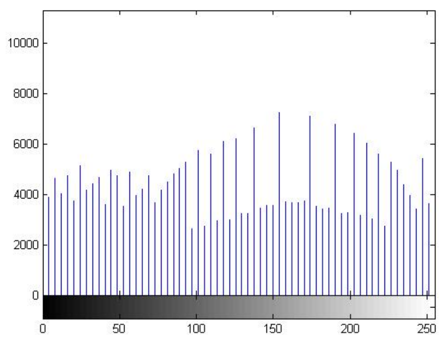
(a) Original image



(b) Equalized image



(c) Histogram of original image



(d) Histogram of equalized image

Figure 3.5: Histogram equalization applied to original image

The original image (Figure 3.5(a)) has low contrast, with most values in the middle of the intensity range. Histogram equalization produces an equalized image (Figure 3.5(b)) having values evenly distributed throughout the range.

The distribution of the histogram of original image (Figure 3.5(c)) are collected in a certain area. The histogram of the equalized image (Figure 3.5(d)) values are more evenly distributed.

3.2.4 Morphological Operations

Morphological operations are widely used in image processing operations that process images based on shapes. Morphological operations apply a structuring element(SE) which consists of a pattern specified as the coordinates of a number of discrete points relative to some origin. Dilation and erosion are most basic morphological operations.

Dilation and erosion are opposite operations of each other. Dilation adds pixels to the boundaries of objects according to SE in an image. Erosion removes pixels on object boundaries of objects according to SE in an image.

Dilation and erosion by themselves are not very useful in grayscale image processing. These operations become powerful when used in combination such as morphological opening and closing. The morphological close operation is a dilation followed by an erosion, using the same SE for both operations.

3.3 Proposed Method

The method we suggested in this thesis project is aiming for finding the defects in the fabric by applying the methods, which was mentioned in previous sections, in a consecutive way. The order of the methods can be seen in the flowchart (Figure 3.6). In this chapter, we cover how we use these methods and what is our approach in development.

Magnitude of the spatial domain image informs us about the geometric structure of image. In the most of the process we are going to benefit from particularly this output of FT. We built our approach on very simple basics. We relied on

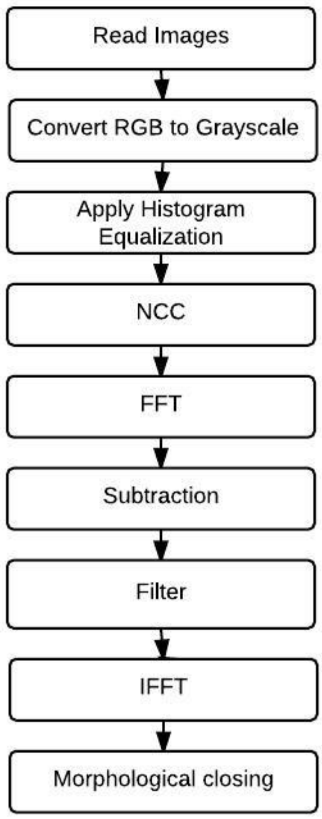
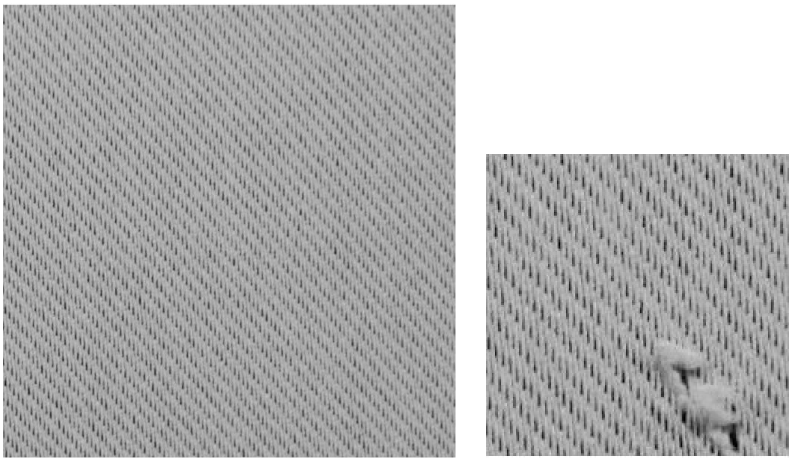


Figure 3.6: Flowchart of proposed method

the fact that we can excerpt the defected area easily by comparing the frequency domain with the expected one. There has been also some enhancements in the intermediary steps in order to get more relevant results based on our needs.

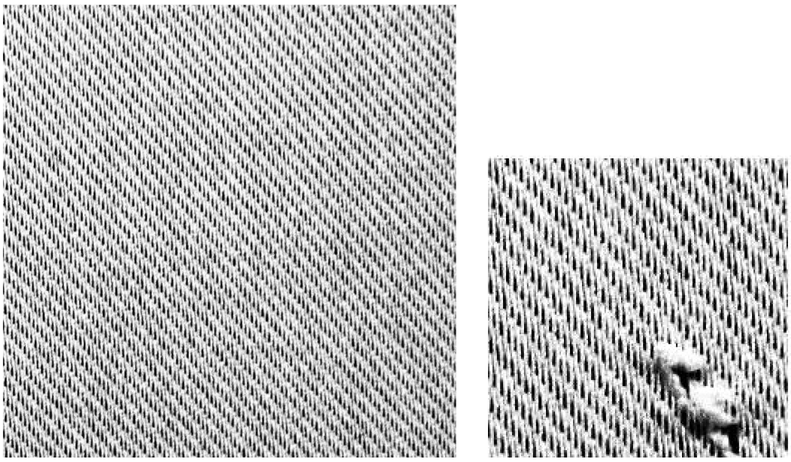
Step by step explanation of our methods and our reasons to use them.

The main requirement of our approach is to have a reference image (Figure 3.7(a)) that we can compare with each fabric. We convert the reference image and the expected image (Figure 3.7(b)) from RGB to grayscale. The other advantage of avoiding the use of RGB is the performance gain since it is expensive to process RGB. Geometric structure and grayscale values will be enough for our approach to detect defected fabric. After this process we enhance the contrast values via histogram equalization (Figure 3.8(a))(Figure 3.8(b)).



(a) Reference image (500x500) (b) Expected image (200x200)

Figure 3.7: Reference and expected images



(a) Equalized reference image (b) Equalized expected image

Figure 3.8: Histogram equalization applied to reference and expected images

In order to do comparison, we create the example area from the non-defect image using NCC (Figure 3.9). We do that to avoid the case when example set covers some part of the pattern which leads to get very different output whether it is defected or not.

By applying FT to non-defect image we switch to frequency domain from spatial domain (Figure 3.10(a)). In this stage magnitude and phase values of the image on frequency domain is kept as reference. Then, the image to be compared is also switched to frequency domain (Figure 3.10(b)) by same approach.

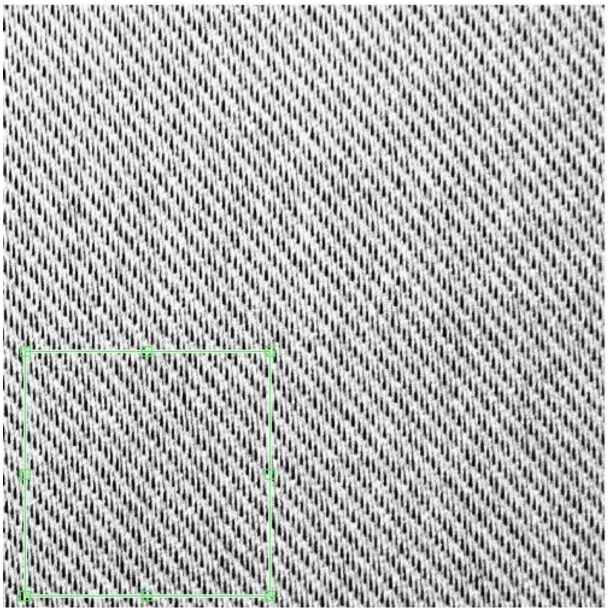
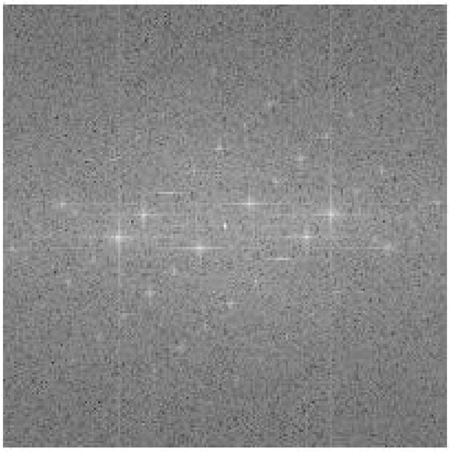
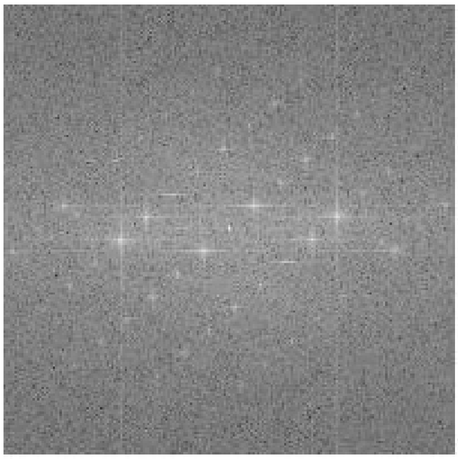


Figure 3.9: Display matched area on reference image



(a) Magnitude of reference image



(b) Magnitude of expected image

Figure 3.10: Magnitude of reference and expected images

Although we only use magnitude of the image in this stage, we also keep phase value since it will be needed in the further stages to re-transform via IFT.

In our approach, when we substract (Figure 3.11) the expected magnitude from input image magnitude, only defects will remain. After the substraction process, we apply two-dimensional image filter (Figure 3.12) to leave peak values on the output.

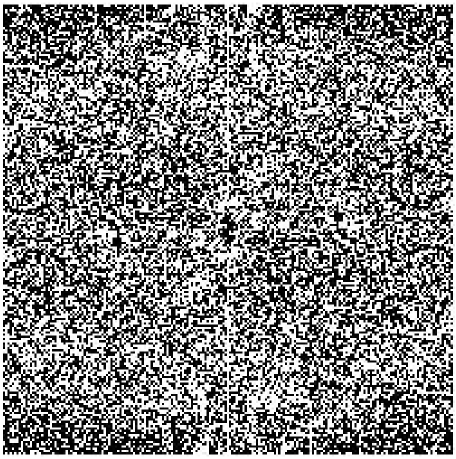


Figure 3.11: Substraction of magnitudes

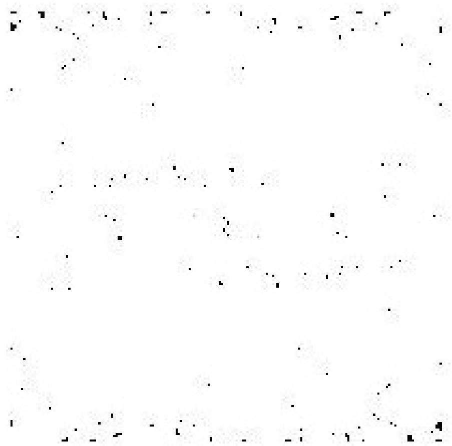


Figure 3.12: Applied averaging filter

We switch to spatial domain from frequency domain via inverse fast Fourier transform(IFFT) (Figure 3.13).

The morphological closing operation which uses 5x5 square SE, is (Figure 3.14) applied to output. After these processes we also filter out tolerable differences and acquire smoother output.

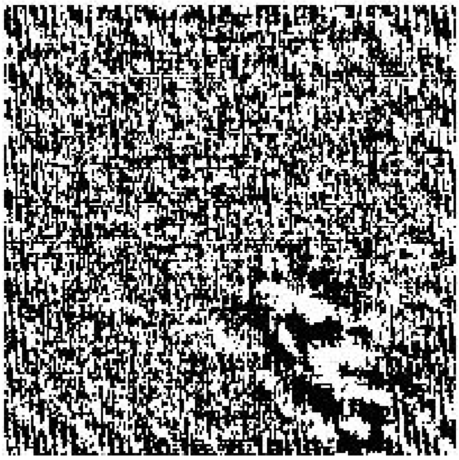


Figure 3.13: re-transform of subtraction image via IFFT

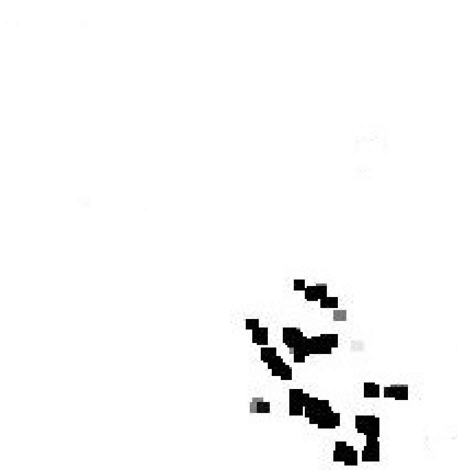


Figure 3.14: Applied morphological closing

Chapter 4

Results and Discussions

4.1 Introduction

In this chapter, we are going to explain details of the image database that we put together. Then we are going to show stages of the tests we have made by using this database step-by-step. Later, we are going to evaluate the performance of our suggested method on different patterns and defects. Finally due to the coherence between our project and paper [2], we also look closer to similarities and distinctions between these two researches.

4.2 Image Database

As we have mentioned before, one of the purposes of our thesis is creating an image database. The database we have created only consists our own images and had been taken on the quality assurance machine of a textile factory. Due to lack of benchmark database on fabrics, we endeavoured to create one. In this study, we also aim to create a benchmark database on fabrics to be used in the future image processing researches.

To have an overlook to technical details of our image database, overall it consists 262 images, where 56 of them are non-defected and 206 of them are defected. There are 14 different patterns and 20 unique defect types. The example set of

Pattern	Non-defect	Broken End	Thick and Thin Places	Broken Pick	Local Distortion	Stain	Slub	Oil Stain	Oily End-Weft	Gout
1	6	6		4						
2	8		3						1	
3	3	10			5			2	6	
4	3			8		6		2	2	
5	2	24								
6	7	1	4	2	10		10	1		2
7	2	7								
8	2	3								
9	1							4		
10	10				1					3
11	1									
12	4	3		5			4	3		
13	5									
14	2						5			
Total	**56**	**54**	**7**	**19**	**16**	**6**	**19**	**12**	**9**	**5**

Table 4.1: Distribution of defect types in image database

defect types can be seen at tables (Table 4.1)(Table 4.2). Every image is size of 5184x3456 pixels. While the classification is made, we also consider patterns and defect types beside marking the picture defected/non-defected. Thus, we can also analyze the success of our method by their defect types and patterns on our tests.

Images are named in the format of "Pattern_DefectOrNot_DefectTypeName (Order)". Thanks to this approach our application will not need any extra work for retrieving the images from our database. E.g. "P1_D_BrokenEnd (1)", "P1_ND (1)"

This common database also provides us the possibility of comparing other similar researches and distinguish the performances between methods. This would enlighten us on the possible co-operations of these existing approaches in order to achieve more reliable and solid defect detection system.

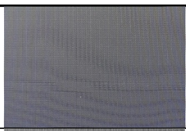
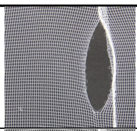
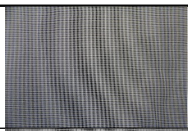
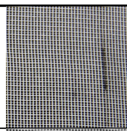
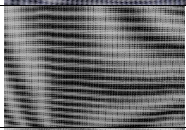
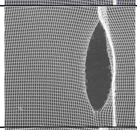
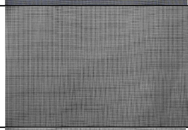
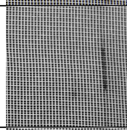
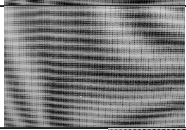
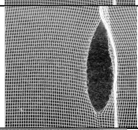
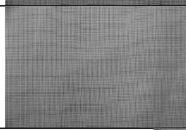
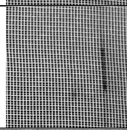
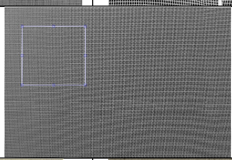
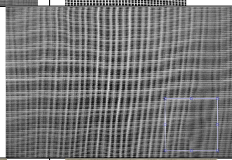
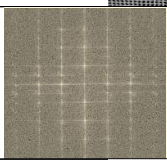
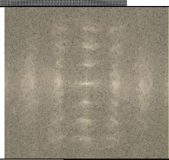
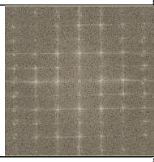
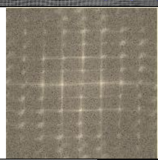
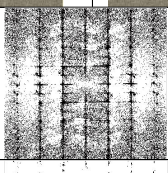
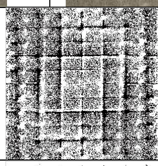
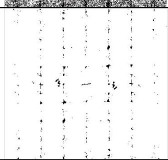
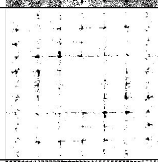
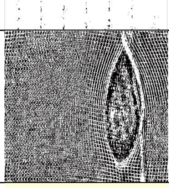
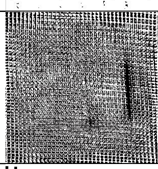
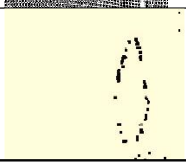
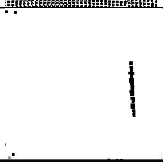
On (Table 4.3), it shown step-by-step applying process of the method, which is explained in Chapter 3, that we used non-defected and defected examples from

Pattern	Hole	Tear	Thick End	Double End	Thick Weft	Tight Weft	Weft Bar	Knot	Color Big	Color Small	Float End
1		2	2								
2											
3				2	1	3	2				
4											
5					2			2			
6						3	3				
7											
8											
9											
10	4										
11							2		10	6	
12											
13	5										
14											10
Total	**9**	**2**	**2**	**2**	**3**	**6**	**7**	**2**	**10**	**6**	**10**

Table 4.2: Distribution of defect types in image database (contd)

two different patterns from image database. So that the process of the method can be easily read over table all at once.

Table 4.3: Step-by-step process of proposed method

	Pattern 1		Pattern 2	
	Reference	Expected	Reference	Expected
Images				
Grayscale				
Equalization				
NCC				
FFT				
Subtraction				
Filter				
IFFT				
Closing				
End of Table 4.3				

4.3 Results

At this part, we are going to test our method and evaluate the results. Patterns and defect types is going to be assessed. Our goal is creating a new defect detection approach which works independent both from any pattern or defect type. We adopted a generic approach that reconstructs global images to detect defects. However, since there are varieties of patterns and defect types, it came up to be not easy to process with our own real image based database. We faced difficulties because of little-sized defects while detection process. The reason is the way of our approach focuses on periodicity on the fabric and little-sized defects sometimes do not corrupt periodicity enough. Result analysis of tests using our image database will be given below. Than we are going to discuss about the success and achievement of our approach and also going to discuss how to improve it in a better way.

We caught different results when we tested different non-defected images on the same pattern. The reason is the time and machine differences, when we shot the images for the database, causes changes on the image background. For example, when one machine has a black background another has white one. Thus, even though the patterns are the same, it has been shown difference during transforms and processes. When background changes, the system keeps on distinguishing the defect but the noise increases on image. It is possible to avoid noise by reducing SE size during morphological closing process. However, we are not working on different sizes of SEs due to our approach's goal which is to detect defects independent from defect type.

If the design on the woven changes according to yarn, it gets harder to detect defect on the fabric if it is any. In our database, Pattern-12 is an example for this case of product. Thick and colorful yarn has been used for the design creation so that the shape and the unstability of the color causes us a lower ratio of detect defect on this pattern rather than to others. We detect the design on the fabric as a defect in some test results because the design disturbs periodic regularity

Table 4.4: Analyze of test results

Defect Type	**Number of Samples**	**Succeeded**	**Success Rate**
Tear	2	2	100%
Knot	2	2	100%
Oil Stain	12	11	91,7%
Non-defect	56	51	91,1%
Hole	9	8	88,9%
Broken End	54	45	83,4%
Color Big	10	8	80%
Stain	6	4	66,7%
Oily End-Weft	9	6	66,7%
Thick Weft	3	2	66,7%
Slub	19	12	63,2%
Local Distortion	16	10	62,5%
Float End	10	6	60%
Color Small	6	3	50%
Broken Pick	19	9	47,4%
Gout	5	2	40%
Tight Weft	6	2	33,4%
Thick and Thin Places	7	2	28,6%
Weft Bar	7	1	14,3%
Thick End	2	0	0%
Double End	2	0	0%
Total	**262**	**186**	**71%**

by itself. In some of our successful case results on this pattern, we were able to detect obvious defects but these have noise.

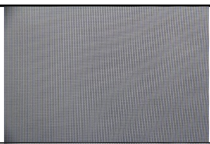
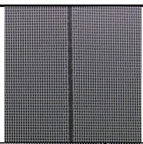
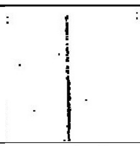
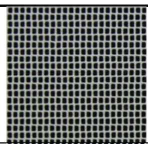
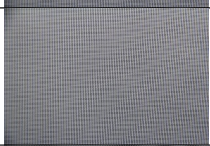
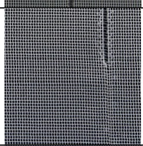
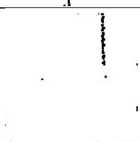
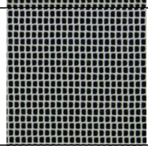
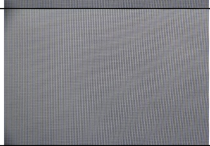
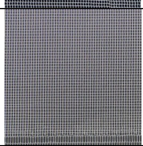
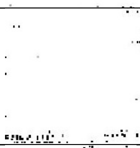
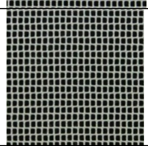
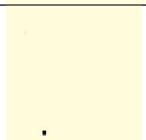
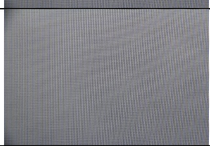
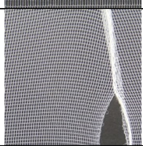
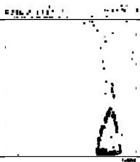
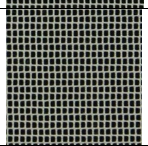
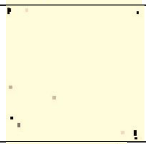
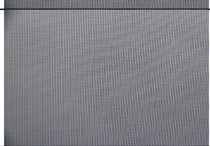
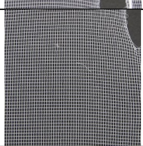
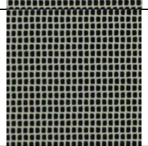
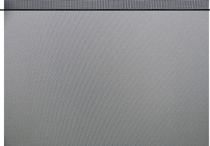
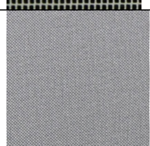
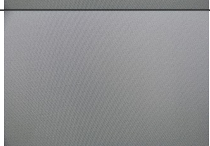
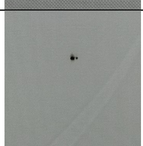
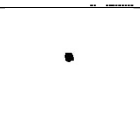
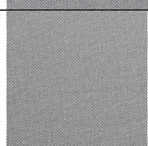
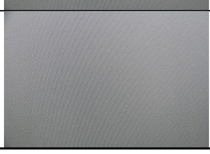
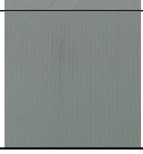
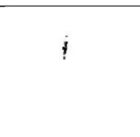
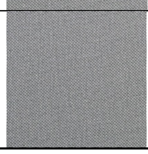
(Table 4.4) shows the analyzes of the tests' results which includes distribution of defect types. It also shows number of examples and their success rate from the tests.

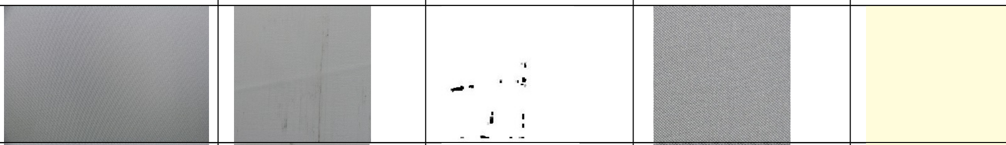
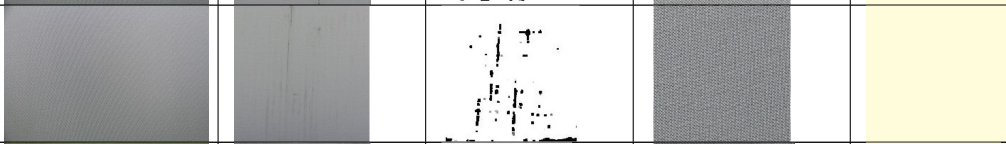
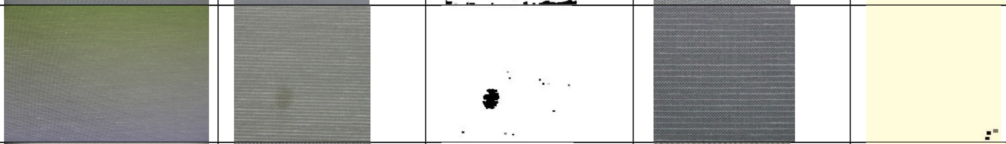
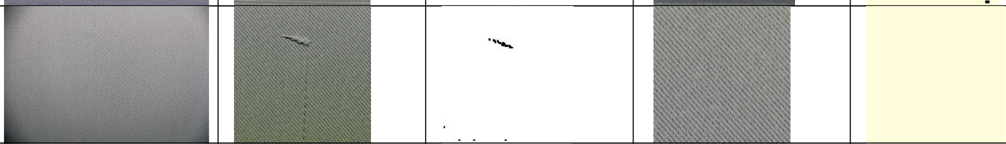
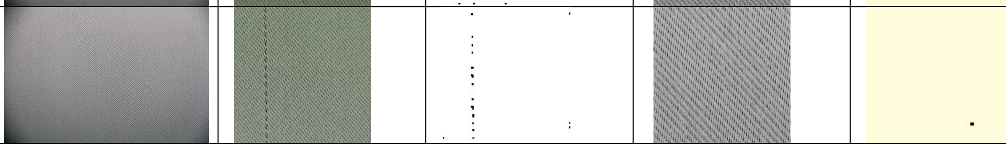
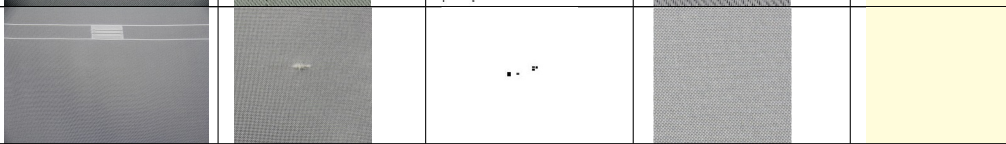
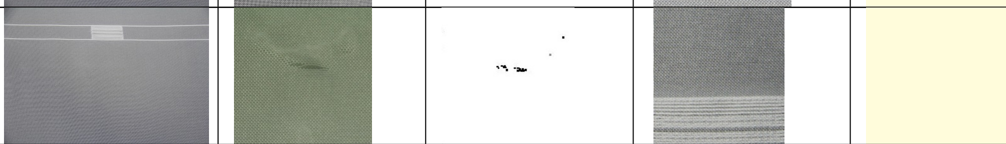
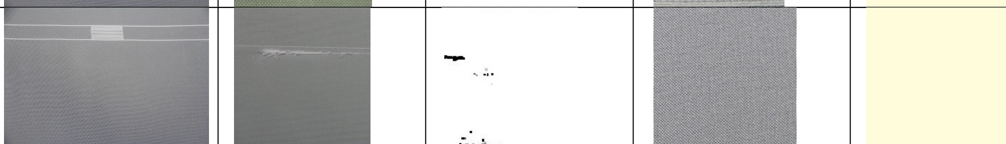
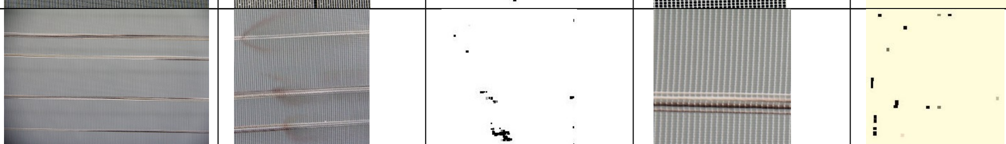
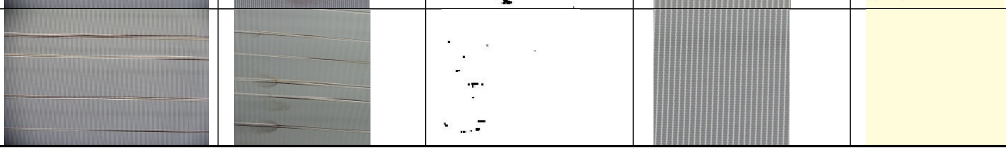
When we examine the test results from the table, we can see the success rate changes due to the defect types. It shows us, on common defect types such as oil stain, hole etc. our success rate is high as we expected. However, some types e.g. weft bar, thick end etc. are outnumbered because the factory, where we collected our image database, has these kinds of defects very rarely. Success rate can be higher for these kinds of types by increase the number of examples and tests. The patterns of common defect types and non-defected ones gives us higher than 80% success rate.

We analysed of 200 samples by using 1926x864 pixels non-defect and 300x300 pixels defect images. An arithmetic average of results is 0.827 seconds. We calculated the standard deviation between samples and the average and it results 0.026 seconds.

(Table 4.5) shows sample test of reference and expected images which inputs to the our method and how they are resulted as output.

Table 4.5: Sample test results

Ex	Reference	Defected	Result	Non-Defected	Result
1					
2					
3					
4					
5					
6					
7					
8					

Continuation of Table 4.5					
Ex	Reference	Defected	Result	Non-Defected	Result
9					
10					
11					
12					
13					
14					
15					
16					
17					
18					
19					
End of Table 4.5					

4.4 Discussions

When we examine the Tsai and Huang [2], appeared to us that this is the closest research to ours. Both researches are focused on the defects that breaks the pattern. They both assume that after ignoring local features, we focus on global image reconstruction and process the image on the frequency domain, the output of IFT will be only defects. Although our approach on retrieving defects is same, the methods we use differs from each other. Tsai and Huang eliminates repetitive patterns by drawing a circle with a diameter of r_max at the middle of Fourier spectrum image, and setting pixel values of the area left out of the circle to 0. They assume output of the restored image from IFT will be local anomalies. How to calculate r_max is explained on their paper. They also mention that their method will only be used on homogeneous surfaces. In our approach, we assume only local anomalies are left by restored image from IFT which is subtracted between defected and non-defected Fourier spectrum images.

Chapter 5

Conclusions

5.1 Conclusions

Developments and innovations in technology has been increasing day by day. Its reflections to the textile world is for sure huge as in many other areas. Therefore, advancing in production rate and speed causes regular ways unstable or defective. Traditional inspections are insufficient in quality control level in textile production. Improved and accelerated ways of image processing methods are became enforced tools to have better solution for detection. Today, there are many researches about this area and keep developing.

Our aim in this research is creating a system which automatizes quality control management as the industry in need. When we studied existing researches, we learned a lot of methods about our subject. However, those methods generally dependent on specific woven and defect types. We set our goal to design a wide range application which is independent from any kinds of woven or defect types. After a detailed study and evaluation, we decided to use FT without finding local features to get the best result to detect defects.

We aimed to have only defected area by subtracting magnitudes of expected and reference images, which is way that has not been used in any other researches which we observed. We adopted this purpose is the main approach of our method. Nevertheless, only this approach was not going fulfill our purpose therefore we used different basic image processing methods e.g. filter, morphological closing, etc. to support it. Thus we have created our method.

We needed an image dataset to test the method we created but we were unable find a proper one. Therefore, we collected proper images which contains different patterns and defect types in textile factory to create a database. It will be made available to future researchers of the field.

We achieved certain results by testing our method with the database we created. Generally, we had successful outcomes but also we experienced difficulties to detect little sized or very indistinct defects. We had 70% success rate on overall database but this ratio got over 80% when we sampled on common defect typed images. We expect that new additions to the database relatively frequency of defects, will raise these rates higher.

We can say that the method we proposed is successful. Defection can be detected independently from its defect type by only entering the non-defected image to the system without any further extra process. At this aspect, system can be able to use without any previous preparation. Hence, our method can be implemented in textile industry as a defect detection system by virtue of its performance and feasibility.

5.2 Future Works

However, our method results decent outcomes, we realized that new features can be added while we were in developing phase. We believe our method can has a valuable spot in the field by its sustainability and being open to be develop.

The only input that our system needs is a non-defected image. We faced noise because time and machine background difference between non-defect and expected image sampling during our test. As a way of prevent it, we are thinking about to use only expected image and than produce an average Fourier spectrum image. Since we can use it as a non-defected image and have more generic system.

We are planning to enrich and improve our database which is effortful and time consuming process, for the future usage. Also by focusing on rare kinds of defects, we are aiming to have comparable close numbers of patterns and defect types samples.

By this study, we only focused on detecting defects but defect types classification is also in our improvement plans. We were thinking about implementing a classification process by using neural network or other methods that we encountered on the researches which we observed.

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