ÇUKUROVA UNIVERSITY
INSTITUTE OF NATURAL AND APPLIED SCIENCES

**Msc THESIS**

**Ahmad Mones NAWAF**

# DEVELOPMENT OF A NEW SOFTWARE FOR FABRIC DEFECT DETECTION AND CLASSIFICATION USING IMAGE PROCESSING AND MACHINE LEARNING METHODS

**DEPARTMENT OF COMPUTER ENGINEERING**

**ADANA, 2019**

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We certify that the thesis titled above was reviewed and approved for the award of the Master of Science degree by the board of jury on

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**DEDICATION**

**...to my father.**

## ABSTRACT

## MASTER THESIS

**DEVELOPMENT OF A NEW SOFTWARE FOR FABRIC DEFECT DETECTION AND CLASSIFICATION USING IMAGE PROCESSING AND MACHINE LEARNING METHODS**



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**ÇUKUROVAUNIVERSITY**
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Quality control in the fabric industry involves a set of standards or guidelines that help guarantee a product meets certain parameters as well as customer satisfaction. Fabric defect detection (also called inspection) is a quality control process aimed at identifying and locating defects. The aim of this thesis is to build an application based on image processing and deep learning methods to automatically detect the defects on the fabric surface and classify them. Discrete Fourier transform (DFT). Normalized cross-correlations, homogeneity equalization, and Gabor filters have been used in image processing, Faster Region Proposal Networks (Faster-R CNN) has been used in classification. The mean square errors (RMSE's) has been used for computing the detecting and classification errors. Based on the results obtained, it has been proved that image processing methods especially DFT can be used for the defect detection with acceptable results.



**Keywords**: Image Processing, Deep Learning, Fabric Defect Detection, Classification.

## ÖZ

### YÜKSEK LİSANS TEZİ

### GÖRÜNTÜ İŞLEME VE MAKİNE ÖĞRENME YÖNTEMLERİ KULLANARAK KUMAŞ HATA TESPİTİ VE SINIFLANDIRMASI İÇİN YAZILIMIN GELİŞTİRİLMESİ

**Ahmad Mones NAWAF**

**ÇUKUROVA ÜNİVERSİTESİ**
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Kumaş endüstrisindeki kalite kontrol, bir ürünün belirli parametreleri ve müşteri memnuniyetini karşılamasını garanti altına almaya yardımcı olan bir dizi standart veya kılavuz içermektedir. Kumaş hatası tespiti (inceleme olarak da bilinir), kusurları belirlemeyi ve kusurların yerlerini belirlemeyi amaçlayan bir kalite kontrol sürecidir. Bu tezin amacı, kumaş yüzeyindeki hataları otomatik olarak tespit etmek ve sınıflandırmak için görüntü işleme ve derin öğrenme yöntemlerine dayalı bir uygulama oluşturmaktır. Kusur tespitinde Fourier dönüşümü (DFT), Gabor filtreleri kullanılmış, (Fast-R CNN) sınıflandırmada kullanılmıştır. ortalama kare hataları (RMSE'ler) tespit ve sınıflandırma hatalarını hesaplamak için kullanılmıştır. Elde edilen sonuçlara dayanarak, görüntü işleme yöntemlerinin, özellikle DFT'nin hata tespitinde kabul edilebilir bir doğrulukla kullanılabileceği kanıtlanmıştır.

**Anahtar kelimeler**: Görüntü İşleme, Derin Öğrenme, Kumaş hata Tespiti, Sınıflandırma.

## GENİŞLETİLMİŞ ÖZET

Teknoloji gelişimi günden güne artıyor. Tekstil kelimesinde birçok yenilik var. Bu nedenle, tekstili denetlemenin geleneksel yolları, tekstilin hem üretim kalitesini hem de hızını arttırmayı devre dışı bırakır. Bu çalışmanın amacı, kumaş fabrikasında kalite kontrolünü incelemek ve tespit etmek için bağımsız bir sistem oluşturmaktır. Bu sistem insanlı kalite kontrol sisteminin yerini alacaktır. Bu sistemi kurmanın nedenleri, müşteri ihtiyaçlarını en iyi şekilde karşılayan daha kaliteli kumaş üretmenin nedeni olan kalite kontrol doğruluğunu arttırmak ve kalite kontrolünü otomatik hale getirirken üretim prosedürünün maliyetini en aza indirmektir. Sistem ve işçi sayısını azaltıp. Literatür taramasında ilgili araştırmaları inceledik, deneylerinden faydalandık ve birkaç nokta elde ettik. Kumaşlar genel olarak periyodik desenlere sahiptir, bu nedenle Fourier dönüşümünün hata muayenesi ve tespiti için çok etkili bir yaklaşım olduğunu tespit ettik. Bununla birlikte, FT özellikleri temeldir, başka bir deyişle, hatanın yerini ve türünü net olarak belirlemezler. FT bazlarının sonsuz bir uzunluğu olduğundan, spektralın her bir bileşeninin katkısını ölçmek pahalı bir işlem olacaktır. Genel olarak, FT tabanlı sistemler belirtilen özellikleri elde etmek için sinir ağlarını kullanır. Aslında, bu özellikleri almak için her zaman sinir ağını kullanmaya gerek yoktur. Çalışmalardan bazıları Local Fourier Transform LFT kullanılarak bir kumaş tanımlayıcı geliştirmiştir. Literatür taramasında, bu yaklaşımlar arasında karşılaştırma yapmak için ortak bir standart veri bulunmadığını bulduk. FT'ye dayalı bazı çalışmalar ancak yeterince test edilmediğini, diğerleri ise bilinmeyen güvenilirliğe rağmen başarılı olduğunu iddia etti. Çalışmaların bazıları ortak olarak belirlenmiş veriye sahipti, böylece birbirlerinin yaklaşımlarını karşılaştırma ve analiz etme şansı elde ettiler. Bu araştırmada, insanlı kalite kontrol sistemiyle yapılamayan rasyonel etkinlik sonuçlarıyla hemen hemen tüm küçük kusurların yanı sıra tüm belirgin kusurları inceleyen bir sistem yarattık. İlk önce fotoğraf makinesini seçmeye başladık, kullandığımız dokuma makinesi Starlinger Alpha 6.0 ortalama 128 santimetrelik üretim genişliğine sahip, kullanılan kablo 1-6 milimetre arasında. 2 milimetre aralığındaki arızaların tespit edilmesi gerekir. Sonra 2 milimetre en az 3 piksel sunulmalıdır. Bu hesaplamaya göre, çekilen görüntünün dijital olarak en az 2250 piksel ile temsil edilmesi gerekir. Aynı uzunluk için bir kare alan yakalanmalı, kamera çözünürlüğü en az 2250x2250 = 5 megapiksel olmalıdır. Diğer bir faktör bağlantı arayüzüdür; BMP formatlı bir görüntü 2 saniyeden daha kısa sürede yakalanıp PC'ye aktarılırken, kamera ile PC arasındaki bağlantının en az saniyede 10 megabayt olması gerekir. Diğer bir faktör, pozlama asgari süresi, tanım olarak, pozlama süresi, enstantane hızı ve diyafram açıklığıdır, hareketli nesne ile uğraşırken pozlama süresi, görüntü kalitesini etkileyebileceği için çok önemlidir. Başka bir deyişle, eğer pozlama süresi daha uzunsa, deklanşör yavaşlar, bu nedenle kameranın sensörleri daha fazla ışıktan etkilenirse, görüntü daha fazla bulanıklaşacaktır. Görüntü işlemede, hareketli bir kumaş yüzeyindeki kusurları incelerken, hiçbir ayrıntıyı kaçırmak istemeyiz. Bu yüzden maruz kalma süresi gerçekten önemli bir faktördür. Daha hızlı deklanşöre sahip kameralar genel olarak daha pahalıdır, işi herhangi bir ek ücret ödemeden yapabilecek mükemmel kamerayı seçmek için kamera minimum özelliklerini tanımlamamız gerekir. Sensör çözünürlüğü gibi ortam değişkenlerini kullanarak kamera sensörü maksimum pozlama süresini tahmin ederken, istenen kamera için 2 milisaniye olan maksimum pozlama süresini hesapladık. Hata tespiti üzerine odaklandık ve hata sınıflandırmasından daha öncelik verdik. Zira kusur tespiti kalite kontrol departmanındaki ana problemken, kusur sınıflandırmasının daha az ilgisi vardı. Görüntü işlemede esas olarak amaçlarımıza uygun bir Fourier Transform versiyonunu kullandık. Dijital sinyal işlemede veya DSP'de, Günümüzde her şey veri iken, bazen uzaydan gelen görüntüler, bazen sismik titreşimler…. Bu verilerin insana okunabilir olması için devam etmesi gerekiyor. Bilgisayarlar bu verileri insan tarafından okunabilir sürümüne dönüştürmek için DSP'yi kullanır. Fourier dönüşümü, zaman veya boşluk alanından spektrum alanına kadar bu verilerin işlenmesi için güvenilir bir fonksiyondur. Fourier dönüşümü bu iki temsil arasındaki ilişkiyi verirken zaman ve frekans bu sinyalleri temsil etmenin alternatif yollarıdır. Ayrık Fourier dönüşümü FF'ye benzer ancak dijital verileri işlemek için kullanılır. Ayrık Fourier dönüşümü, Hızlı Fourier Dönüşümüne (FFT) hesaplamak için daha hızlı ve daha verimli bir algoritma diyoruz. Görüntüler iki boyutta olsa da, DFT gibi tek boyutlu bir işlev uygulanmaya uygun değildir. Giriş matrisinin her bir boyutu için Hızlı Fourier Dönüşümünün Hesaplanması, iki boyutlu MxN ile ayrık Fourier dönüşümü uygulamasına eşittir. Lineer bir filtre olan kenar tespiti için Gabor filtreleri kullandık. En önemli kullanım doku analizidir, yani görüntüde belirli bir içeriğin olup olmadığını ve yönelime duyarlı olup olmadığını analiz edebilir.

Yaklaşımımızı yaptığımızda, görüntülerdeki homojen olmadığı için sonuçlar yetersiz değildi, bu tür meselelere bilgisayar vizyonunu kullanarak hataları incelemek gibi hassas bir işte karşılaştığımızda yetersiz sonuçlara yol açabilir. Diğer teorik çalışmaların çoğu, sonuçlara yaklaşan laboratuvar örneklerine dayanıyor ve sonuçları% 100 homojenlik skalasıyla mükemmel bir şekilde taranan laboratuvarı sınırlandırıyor. Işık koşullarının yakalanan görüntüden diğerine değişeceği fabrikada gerçek makinelerle uğraşırken. Histogram eşitlemesi daha da kötüleşebilir. Sabit bir hata saptama sistemi kurmak için homojenlik bir eşitleme geliştirilmiştir. Bu eşitlemenin amacı görüntünün kontrastının ortasını ve köşelerini homojen hale getirmektir. Hata tespitinin yüksekliği doğrulukta olması, sahildeki daha az hedefin yanındadır. genellikle, görüntü işleme işlevleri güçlü bir donanıma ihtiyaç duyar. Tezin bu bölümünde, sonuçların kalitesini etkilemeden süreçlerin kısıtlanması sağlanmıştır.

Eşzamanlı çalışan iki uygulama geliştirdik. İlki, enkoder uzunluğu verilerini PLC'den okumaktan ve her 40 santimetrede bir görüntü yakalamaktan sorumludur. Daha sonra uzunluk verileri ile sabit olarak saklar. İkinci uygulama, ilk uygulamanın hedef dosyasındaki görüntüleri okur. Görüntü işleme CPU'yu kullanabildiğinden ve uygulamanın diğer işlemlere yanıt vermemesine neden olabileceğinden, bu yöntemi eksik kumaştan korumak için kullandık. Yakalama uygulaması, görüntü işleme uygulamasından bağımsız olarak çalışıyor. İlk önce uygulama, diğer görüntü yakalama uygulamasının hedef dosyasından bir görüntü okur, gri tonlamaya dönüştürür, varil bozulma düzeltme yöntemini uygular, homojenlik eşitlemesi uygular, Hızlı Fourier Dönüşümü uygular, normalleştirilmiş çapraz korelasyon uygular, kenarları tespit etmek için Bulunan herhangi bir kusurun kumaş alanı içinde olması halinde çıkarma, ters FFT uygulanabilir, genişliği hesaplamak için başka bir filtre uygulayabileceği, görüntü işleme ile algılanan hata türünü sınıflandırabilir ve karar verebilir. Ardından, yeni çekilen görüntüleri kontrol etmek için hedef dosyanın bağlantılarını güncelleyin. Çekilen fotoğraf yoksa uygulama yeni modda bekleyen boş modda olacaktır. Uygulama, yakalanacak yeni bir görüntüden önce, PC görüntü işleme fonksiyonlarını tamamlayabildiği sürece gerçek zamanlı olarak çalışabilir. Hatalı görüntüler, uygun resim yazısı eklendikten sonra sabit sürücüde saklanır.

Görüntü işleme yöntemlerini ve algoritmalarını ilk defa kullandığımızda, yetersiz sonuçlar elde ettik. Daha iyi sonuçlar elde etmek için ilk yaklaşımı geliştirmek için çalışmaya devam ettik. Kalite kontrolünde önem taşıyan genişlik ölçümü yapmak için bir filtre geliştirdik. Genişlik, belirli değer aralıkları arasında olmalıdır; Çok geniş veya dar kumaş başka bir kusura neden olabilir. Ayrıca, müşterilerin isteklerine göre istenmeyen bir durumdur. Veri setimizde Abdioğulları Plastik ve Ambalaj Sanayii A.Ş.'nin üretim hattından bir alan tarama kamerası kullanılarak yakalanan 1100 örnek vardı. Her biri için genişlik ölçümü ve hatalı numuneler dahil olmak üzere yüz örnek. Bizim yaklaşımımız tespit edilen örneklerin% 94,9'unu tespit etti. Görüntü işleme yöntemleri kullanılarak% 90,5 doğru "yağ lekeleri" ve "makine parçası sıkışmış" kusurları sınıflandırması elde edildi. Verimsiz bir sonuç olarak düşünülebilecek derin öğrenme yöntemi (Faster R-CNN) kullanılarak% 63,5 oranında kusur sınıflandırması elde edildi. Gelecekteki çalışmalarda sınıflandırma etkinliğini arttırmayı amaçlıyoruz.

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## LIST OF ABBREVIATIONS

| | | |
|---|---|---|
| RMSE | : | Root Mean Square Error |
| MAPE | : | Mean Absolute Percentage Error |
| MAE | : | Mean Absolute Error |
| OCC | : | Ordinary Cross-Correlation |
| NCC | : | Normalized Cross-Correlation |
| FTT | : | Fast Fourier Transform |
| IDFT | : | Inverse Discrete Fourier Transform |
| DFT | : | Discrete Fourier Transform |
| DTFT | : | Discrete-Time Fourier Transform |
| FT | : | Fourier Transform |
| PP | : | polypropylene |
| PE | : | polyethylene |
| PLC | : | Programmable Logic Controller |
| LFT | : | Local Fourier Transform |
| WOV | : | Weighted Object Variance |
| R-CNN | : | region standing convolutional neural network |
| BDC | : | barrel distortion correction |

# I. INTRODUCTION

## 1.1. Overview of the fabric industry

In the fabric industry, fabric production is done by weaving and kittening machines. Fabric is usually made of textile fibers. Textile fibers are made with natural sources like animals (wool, silk), plant (cotton, flax, bamboo), synthetic (nylon, polyester… Etc.) or mineral (asbestos, fiberglass…. Etc.) (Maxwell et al 2003).

Fabric defect means a flaw on the fabric surface, as a result of the manufacturing process, and can occur during the processes because of machine defects, yarn faults and/or extreme stretching and machine spoils. There are more than 70 kinds of fabric defects according to the textile industry. Defects can happen either in the motion direction or perpendicular to it. The defects on the fabric surface generally categorized into two terms of quality standards: texture non-uniformity and change in surface color. These two main defect categories can be resulted by a lot of causes like broken machine part, needle break, object spun in yarn during the spinning process, weft curling, oil leakage, using a cord from different type or color …… etc. (Kazim et al 2016)

Quality control in the textile industry has a set of standards or level that help to guarantee the product to meet customer satisfaction. Fabric defect inspection is a quality control process that aimed to detect and locate defects. Fabric factories generally hire a lot of quality control workers in order to keep production quality matching customers' expectations.

Although the traditional inspection has an acceptable accuracy, while a standard fabric quality control machine has at least a width of 120 centimeters which needs one employee for each machine to watch which called a quality specialist. The line movement of the fabric is 5-15meters per second in average, when the employee notices a defect on the fabric surface he stops the machine, marks the defect, writes the length information and starts the machine again. Staring for a long period of time in the fabric can cause eyestrain and daydream over time which can lead to missing some defects or overcounting… etc. Quality control department prefers to do some sample tests instead of monitoring the whole unite.

The production is being examined in two stages by the quality control department:

- Raw Material Control: this check is being performed while the machine producing the fabric. in this stage, defects are caused by the machine or the user.
- Semi Material Control: In this stage quality control is also important for the processed fabric. In here, defects include trimming, yarn, crushing… etc.

Figure 1.1 represents an example of a fabric defect caused by machine head shifting. This defect has happened during fabric production.

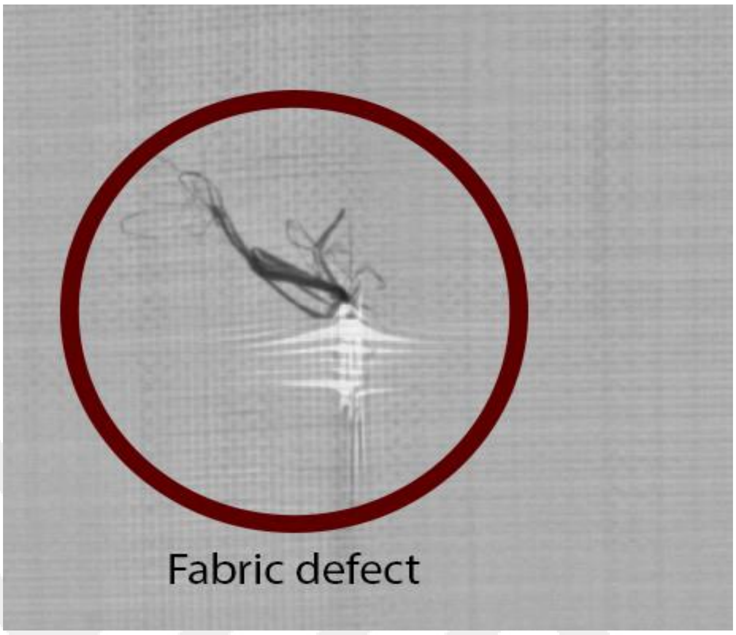



Figure 1.1. Example of a fabric defect

## 1.2. Motivation and Purpose of this Thesis

The aim of the study is to develop a standalone application that can capture pictures of fabric from the running machine process them, detect defects in fabric surface and locate them with high accuracy using image processing methods. And build a model that classifies them using deep learning methods.

The benefits of automating the defect inspection and classification are as follows:

- Defect detection: Gives more accurate and stable results than the manned depended systems that mean the production quality is also improved.
- Classification: classifying the detected defects can help technicians make a more accurate diagnosis for a possible machine breakdown.

- Cost: automating defect detection can cost once for a lifetime while hiring a qualified specialist is not.

This thesis and system equipment setup has been done in ABCO factory.

### 1.3. Literature Review

There are a lot of studies have been done for the aim of fabric defect detection. The late related studies are as follows:

(Shaoqing Han et al 2019) used Gabor filter to detect nonwoven fabric Crease. In their study the have developed a 2D Gabor filter-based method to detect the crease defects. The study depended on the tunable angular and axial bandwidth of the crease defects. Where fabric crease images are transformed to the frequency domain from the spatial one, filter the frequency domain by Gabor filter with adjustable central frequency. Then they reversed to the spatial domain and obtain the defects using blob analysis. They claimed that this method has an accuracy of 60-70%. Their study is restricted to nonwoven fabric and only for crease defects.

(Bo Shi et al 2019) proposed a method based on phase sensitive optical time domain reflectometer (OTDR) distributed optical fiber micro-vibrations sensor, this mechanism detecting the laser intensity change in a standard optical fiber cable hang in the filter bag. Which is the result of the dynamic airflow's perturbation, so this study is based on hardware mechanism. Their method provides an alternative way for inspecting defects on bag fabric. They claimed that their method can be used in coalmine industry as well.

(Li Yuyuan et al 2019) developed a Convolutional Neural Network (CNN) model that detect fabric defects. They used multi-layer perceptron to optimize network. The main component of a micro architecture is constructed using techniques of multi-scale analysis. They improved detection accuracy by using multiple locations pooling, filter factorization, and parameters reduction. they claimed that their method achieved superior performance in terms of detection accuracy with a much smaller model size.

(Xiao-cui et al 2015) prepared a survey that separates the fabric image from the background using a threshold which is a vision-based method. Also, weighted Object Variance (WOV) has been used in this study which results in the distribution of the image histogram change. He also improved and tested Otsu method, which is a computer vision method named after Nobuyuki Otsu that performs clustering-based image thresholding, in defect detection of various surfaces. He finds out that the WOV method provides better segmentation results.

(Yin et al 2009) proposed a method to detect defects such as holes and oil stains. He used wavelets to detect background of the fabric pattern while the flaws remain. the hole type of defects has more white color while the oil stains have a darker color. Then he used a back-propagation neural network with two layers to classify the defects to two groups: stains and holes.

(Kumar A. et al 2008) proposed a study that uses image processing methods to compares fabric defect detection techniques. These techniques categorized as follows: spectral, statistical and model-based. The performance according to his study is highly variable. According to this study, the usage of these features and algorithms produce better results compared to the usage of one of these techniques, and it's recommended for future research.

(Hang et al 2003) suggested a fabric defect detection by applying Fourier transform. This study detects defects not only in fabrics but in any textured surface like leather, sandpaper…. etc. It doesn't find a local defect, so it's based on image reconstruction using FT. While Fourier transform returns spectrum image, this method detects defects by removing repetitive texture patterns using small circular samples from the center. Detecting the defect by finding anomaly out of the restored fabric image.

Fourier transform has importance between image processing methods and algorithms. Fourier transform a mathematical function which decomposes a waveform which can be a function of time into the frequencies that form it up. Using Fourier transform in image processing can convert an image to two-dimensional complex function: magnitude and spectrum. Higher values in the spectrum inform us that recurring pattern/texture and its direction. So, periodic structure on an image is being detected by magnitude spectrum (chi-ho et al 2001). When a defect exists on a fabric, also there will be a corruption in periodicity as well, there for a distinct spot on the spectrum will occur. We can use peaks on the spectrum as features. That will help us to analyze and detect recurring patterns and defects. this method with those features is eligible to be used to inspect and detect defects.

Fabrics have periodic patterns in general, for this reason, Fourier transform is a very efficient approach for fault inspection and detection. Nevertheless, the FT features are basic, in other words, they don't determine neither the location of the defect nor its type (Tsai et al 2003). Because of the FT bases has an infinite length, it would be an expensive process to quantify the contribution from each component of the spectral. Generally, FT based systems use neural networks to get the mentioned features (Henry et al 2011). Actually, there is no need to use neural network always to get these features. (Zhou et al 2001) developed a fabric identifier by using Local Fourier Transform LFT.

As a conclusion of the literature review, there is no common standard data set for comparison between these approaches. Some studies based on FT but they weren't tested sufficiently, the others' claimed as successful despite of the unknown reliability. Some of the studies like Tilda et al 2002 and Henry et al 2011, they had the data set in common so they had the chance to compare and analyze each other's approaches.

### 1.4. Contributions of the Thesis

The major differences between this thesis and the previous studies can be listed as follow:

1. This study is focusing on detecting defects on polypropylene (PP) and polyethylene (PE) materials which are never has been made before.
2. The system is developed for synchronous detection of defects on both sides of the material.
3. The system is running on real weaving machine and tested in a textile factory, a reliable result has been obtained.
4. The system can work in real time, meaning that the defects will be detected in real time, and stored for classification.

# 2.OVERVIEW OF SYSTEM SETUP AND DATASET COLLECTION

## 2.1. Overview of System Setup

The dataset used in this thesis included 1600 fabric images, captured from Abdioğulları Plastic and Packaging Industry Co. in order to capture this number of images a system has been set up.

Figure 2.1 explains the system components and setup. While the fabric has a linear direction movement, a PLC connected to an encoder fetching the length and sending data by Ethernet. Two cameras for each side are connected to the computer to inspect both sides. Lighting panels are fixed to fabric from behind to insure more detailed images.

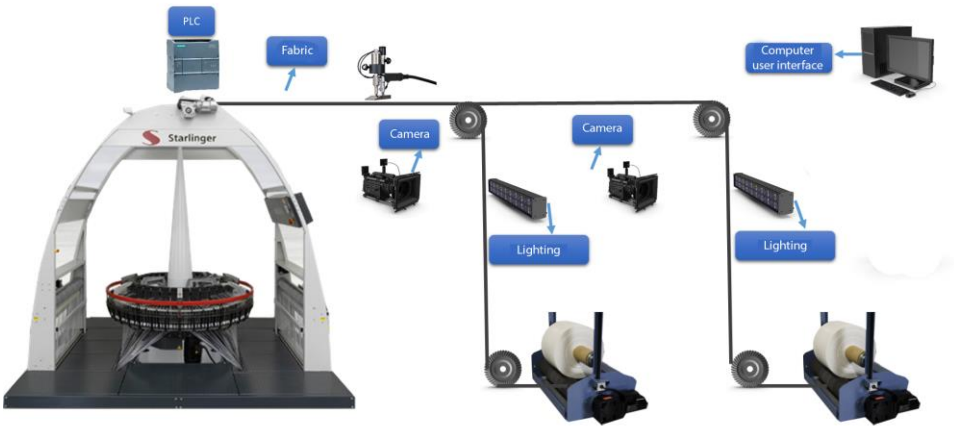



Figure 2.1. System Setup

A computer with a user interface is controlling the image capture, the fabric linear movement speed is approximately 6 meter per minute. The application uses the data from PLC to capture one image every 40 centimeters to make sure all the fabric will be captured then analyzed.

## 2.2 Camera Selection

There are two types of cameras, Line Scan Cameras and Area Scan Cameras. Line scan cameras have one line of sensors, so the image is being formed by combining the scanned on dimensional arrays (lines) into a two-dimensional array. Figure 2.2 represents the procedure of line scanning.

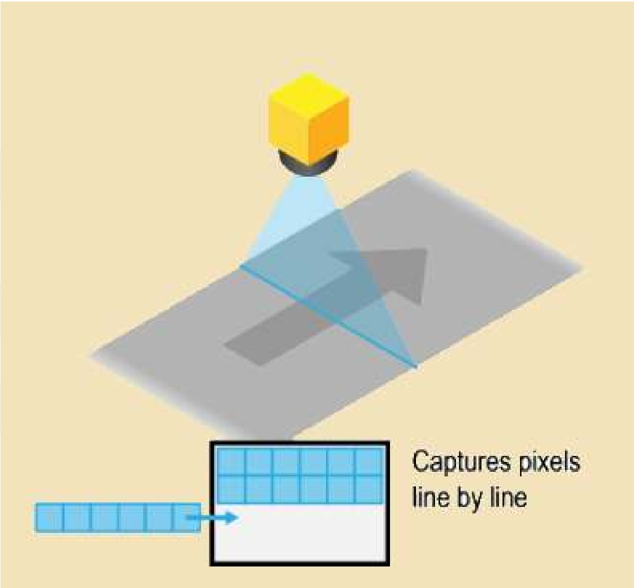



Figure 2.2. Line Scan Camera

While area scan cameras have a two-dimensional array of sensors, so it can scan a two-dimensional area and give a two-dimensional array of pixels by once. Figure 2.3 represents the procedure of area scanning.

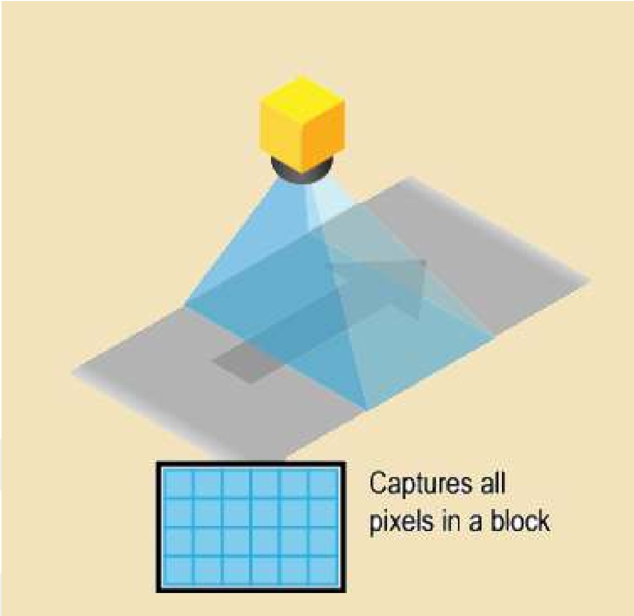



Figure 2.3 Area Scan Cameras

In this thesis, the weaving machine we used Starlinger Alpha 6.0 has the production width of 128 centimeters on average, the used cord is between 1-6 millimeter. Defects of the 2-millimeter range have to be detected. Then a 2 millimeter has to be presented at least by 3 pixels. The captured image after adding the edges would reach 150 centimeters. According to this calculation, the captured image needs to be digitally represented by at least 2250 pixels. The same for length a square area has to be captured, then the camera resolution has to be at least 2250x2250 =5 megapixel. One other factor is the connection interface, while one BMP formatted image has to be captured and transferred to PC in less than 2 seconds, then the connection between camera and PC has to be 10 megabytes per second at least.

Another factor is exposure minimum time, as a definition, exposure time is the shutter speed and aperture, while we are dealing with moving object, exposure time is very important because it can affect the image quality. In other words, if exposure time longer, then the shutter is slower, so the camera's sensors are being affected with more light, the image will have more blur. Figure 2.4 shows the difference between captured images when the exposure time is being changed. In this experiment a pinwheel with stable speed (75 round per minute) is being captured with three different exposure time (figure 2.4 a) is captured with a fast shutter or short exposure time. (2.4b) is captured by a slower shutter or longer exposure time than figure 2.4.a. (figure 2.4c) is captured by longer exposure time than figure 2.4.b.

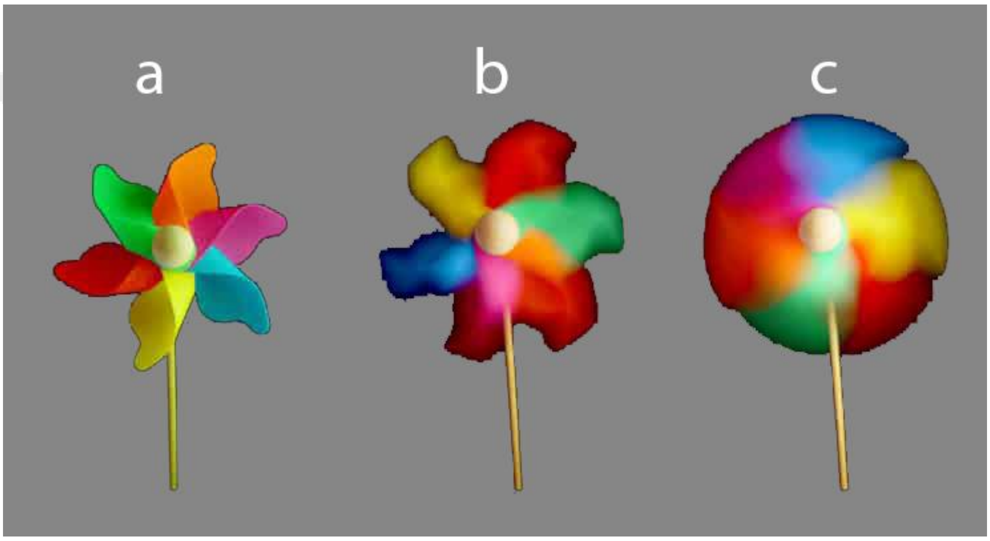



Figure 2.4 Exposure Time Effect

In image processing, when inspecting defects on a moving fabric surface, we don't want to miss any detail. That's why exposure time is really an important factor. Cameras with faster shutter are more expensive in general, we need to identify the camera minimum properties in order to choose the perfect camera that can do the job without any extra costs. Estimating the camera sensor maximum exposure time using environment variables like sensor resolution Y`, the field of view Y, fabric linear speed V and max allowed image blur in pixel A (Figure 2.5). Using 2.1 we can calculate the maximum exposure time for the wanted camera according to (Luk´aˇs Cerman et al 2006) which is 2 milliseconds

$$R = (Y`)/Y \;; \quad R\ is\ resolution\ pix/mm$$
$$B = R/V \;; \ pix/\text{sec}$$
$$S = \frac{1}{b} \quad sec/pix$$
$$E = S \times A \qquad (2.1)$$

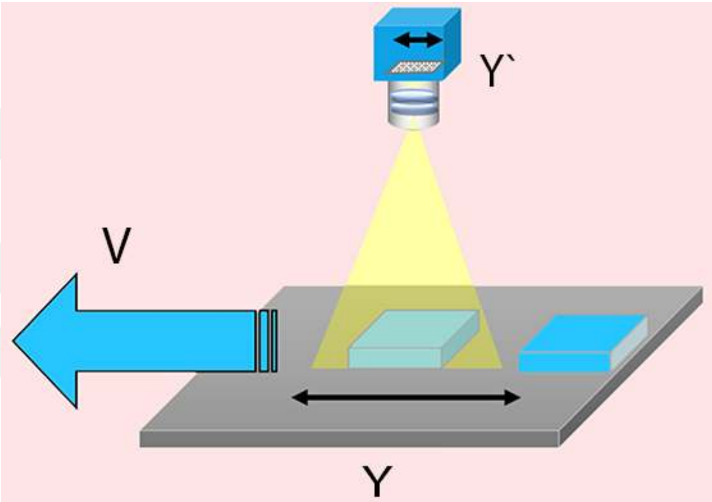


Figure 2.5 Exposure Calculation

According to these calculations SVS-VISTEK exo250CU3 has been chosen for this job for the following reasons:

- Resolution is 5 megapixels: 2448-pixel width x 2048-pixel height then it satisfies the previous condition for width (2448 > 2250).
- Frame rate is 75 fps that means that it can capture 75 frames per second.
- Minimum exposure time is 21 microseconds which satisfy the exposure time condition.

The other device features and technical data are listed in table 1.1 as follows:

Table 2.1 Camera technical data

| | |
|---|---|
| Resolution | 2448 x 2048 px |
| Frame rate (max.) | 75 fps |
| Chroma | Color |
| Interface | USB3 Vision |
| **Sensor** | |
| Sensor | IMX250LQR |
| Manufacturer | Sony |
| Sensor type | Area CMOS |
| Shutter type | global shutter |
| Sensor size (h x v) | 8.45 x 7.07 mm |
| Optical diagonal | 11.01 mm |
| Sensor format | 2/3 " |
| Pixel size (h x v) | 3.45 x 3.45 µm |
| **Camera** | |
| Exposure modes | MANUAL;AUTO;EXTERNAL |
| Trigger modes | INTERNAL;SOFTWARE;EXTERNAL |
| Exposure time (min) | 21 µs |
| Exposure time (max) | 1 sec (external ∞) |
| Pixel format / max | bayer8, bayer12packed / 12 bit |
| Gain modes / max | manual, auto / 48 dB |
| S/N ratio | 40 dB (dep. on environment) |
| Dynamic range | 72 dB (dep. on environment) |
| Internal memory | 256 MB SDRAM, 32 MB Flash |
| **Feature Set** | |
| Manual white balance | Yes |
| Automatic white balance | Yes |
| AOI | Yes |
| LUT | Yes |
| Offset | Yes |
| Binning | Yes |
| Image flip | Yes |
| Sequencer | Yes |
| **Housing** | |
| Lens mount | C-Mount |
| Dimensions (w x h x d) | 50 x 50 x 34.1 mm |
| Weight | 138 g |
| Operating temperature (housing) | -10 to 60 °C |
| Ambient humidity | 10 to 90 % (non-condensing) |
| Protection class | IP40 |
| **I/O-Interfaces** | |
| Input up to 24V | 2 x |
| Input OPTO | 1 x |
| Output open drain | 4 x |
| I/O RS-232 | 1 x |
| Power supply | 10 to 25 V (DC) |
| Power consumption | 4.5 W (dep. on operating mode) |

### 2.3 Data Set Collection

Interface software is made using C# in order to control the camera and capture images in time. The data set contains the most frequent defects which's made intentionally by means of an expert technician, the collected defect samples are represented in table 2.2 as follows:

Table 2.2. data set contents

| **Defect** | **count of samples** |
|---|---|
| Broken yarn | 100 |
| yarn collapse | 100 |
| Machine part got stuck or oil stain | 100 |
| Broken fabric | 100 |
| Broken warp | 100 |
| The usage of different type of rope | 100 |
| Folding | 100 |
| Cord shifting | 100 |
| missed warp (one or more) | 100 |
| missed yarn (one or more) | 100 |
| Node in fabric | 100 |
| Machine head shifting | 100 |
| Rarity in yarn | 100 |
| None defected fabric | 100 |
| Width mesurment test | 100 |

As it's clear, 100 images have been captured from each defect type. The last one "width measurement test" has been captured, measured and labeled to ensure the efficiency of width measurement methods. "none defected fabric" has been captured to be analyzed and evaluated by the algorithms. Defect types according to the reason are as follows:

- Broken yarn: when a weft yarn is broken in the fabric it appears as a defect. The probable reason for this defect is one of the following: shuttle box, incorrect or rough placement of the shuttle eye, loose of the pirn in the shuttle, weak yarn strength, incorrect alignment of the pirn and rough surface of shuttle. Figure 2.6 shows broken yarn defected fabric.

Figure 2.6 Broken yarn

- Yarn collapse: yarn overlap is considered a defect; it can be caused by one of the following reasons:
  - Low pressure at the posture wrapper
  - Opened periodic frequency.

And it can be fixed by either setting the pressure to its right value or close periodic frequency. Figure 2.7 represents yarn collapse defected fabric.

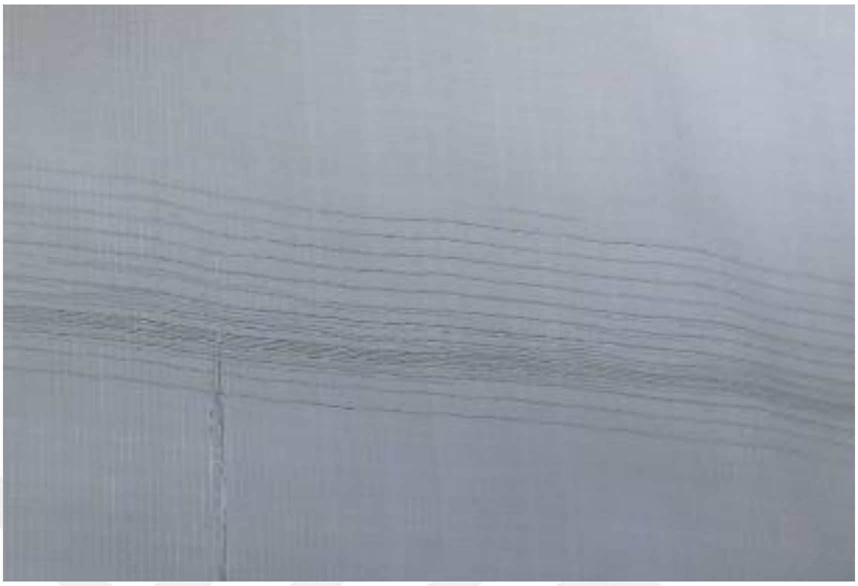


Figure 2.7 yarn collapse

- Machine part got stuck: when a machine part such a spring get stuck to the fabric it causes damage in the fabric which is a defect. figure 2.8 shows a spring got stuck in the fabric and caused some damages.

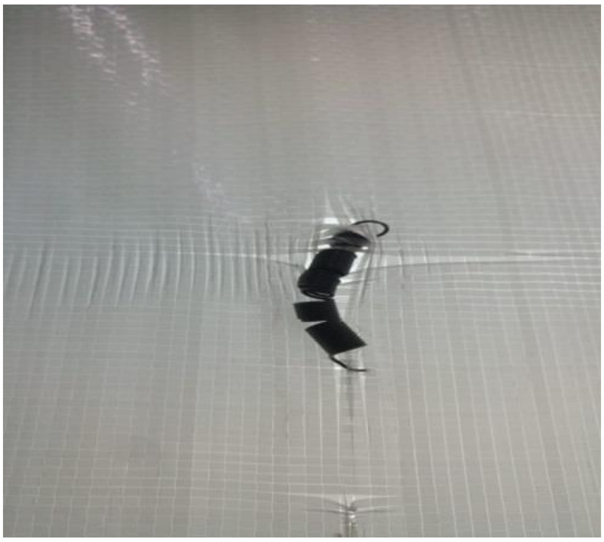


Figure 2.8 machine part got stuck

- Oil stain: oil is used to reduce friction in the spinning or moving machine parts when oil leakage happens it will cause stains in the fabric, it's an unwanted defect. Adjusting the machine will prevent these kinds of defects. Figure 2.9 shows a stained spot in the roll of fabric.

Figure 2.9 oil stain

- Broken warp: it is caused by one or more from the following factors:
  - Frequency is more than the theoretical frequency
  - Tape width is greater than theoretical
  - Uneven distribution of warp cord

It can be fixed by adjusting the frequency, change the tape width to the proper one or even distribute the warp cord. An expert technician does these fixes. Figure 2.10 shows broken warp sample.

Figure 2.10 Broken Wrap

- The usage of different type of cord: including using cords with different color or width which can make disproportionate weaving which is count as defect. We can get rid of this kind of defects by locating the odd cord bobbin and change it with the right one. Figure 2.11 shows an example of defect of that type.

Figure 2.11 The Usage of Different Type of Cord

- Folding: can be caused by the following reasons:
  - Width narrowing or expanding
  - Unadjusted butterfly sleeve

This fault can be fixed by adjusting the butterfly sleeve and control the width. Figure 2.12 represents this type of defects.

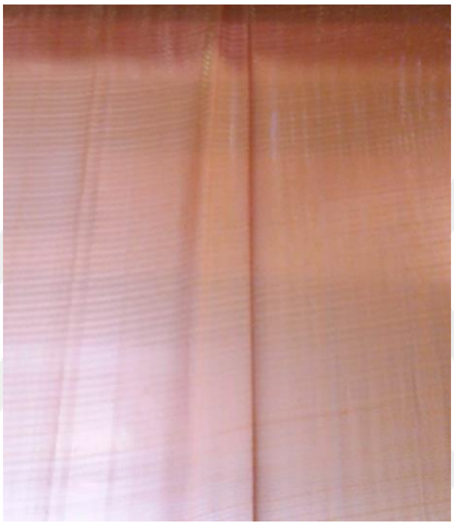


Figure 2.12 Folding

- Cord shifting: this defect is the result of the following causes:
  - Width narrowing or expanding
  - Unadjusted butterfly sleeve

This fault can be fixed by adjusting the butterfly sleeve and control the width. Figure 2.13 represents this type of defects.

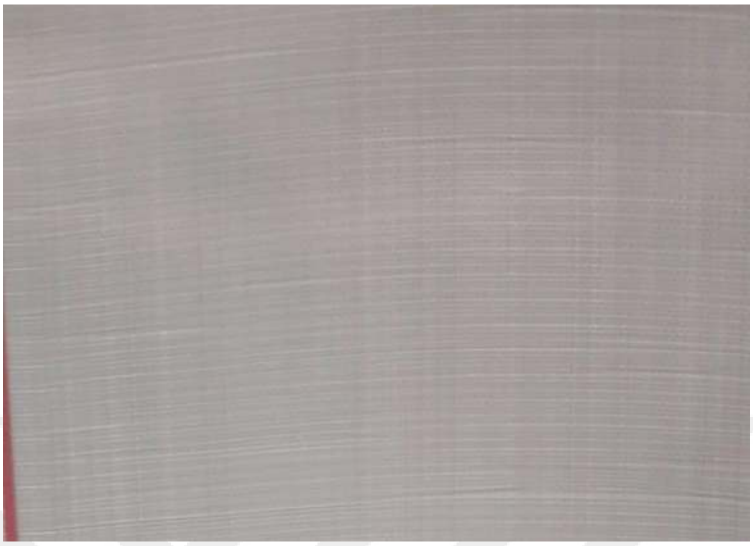


Figure 2.13 Cord Shifting

- Missed Warp (one or more): This is the case when the machine continues production after the weft bobbins are finished or the cord ruptured (Sensor may be faulty or disabled). It can be fixed by checking the bobbins for such a problem and fix it or simply checking the sensors periodically. Figure 2.14 shows an example of this kind of defects.

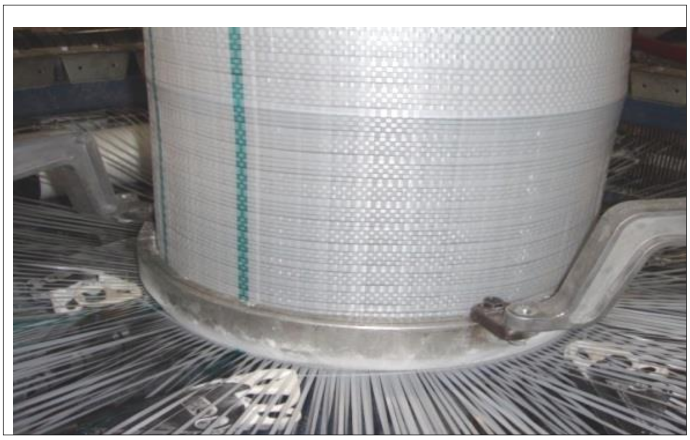


Figure 2.14 Missed Warp

- Missed Yarn (one or more): It occurs when the warp rope breaks during production and machine continue the production. It can be fixed by checking the related sensors periodically. Figure 2.15 represents a defect of that type.

Figure 2.15 Missed Yarn

- A node in Fabric: this kind of errors happen when the worker does not cut the node after changing the bobbin. It can be avoided by checking the cords after changing the bobbin. Figure 2.16 shows an example of this type of faults.

Figure 2.16 Node in Fabric

- Machine Head Shifting: it can be the result of:
  - the rope falls to the sides
  - burr formation in the ropes

There is no solution to avoid this kind of defects yet. Figure 2.17 shows an example of this kind of defects.

Figure 2.17 Machine Head Shifting

- A rarity in Yarn: it can be caused by two factors.
  - The sleeve is not adjusted properly.
  - The use of wrong rope width.

This kind of defects can be avoided by checking the sleeve settings and the rope width periodically. Figure 2.18shows rarity in yarn defect.

Figure 2.18 Rarity in Yarn

- Broken Fabric: it can be caused by one of the following reasons:
    - Weft Break
    - Warp Break
    - Mechanical Failures
    - Errors in Bobbin

And it can be fixed by fixing the related mechanical failures, checking bobbins, reattach weft rope or reattach warp rope. Figure 2.19 shows an example of a broken fabric.

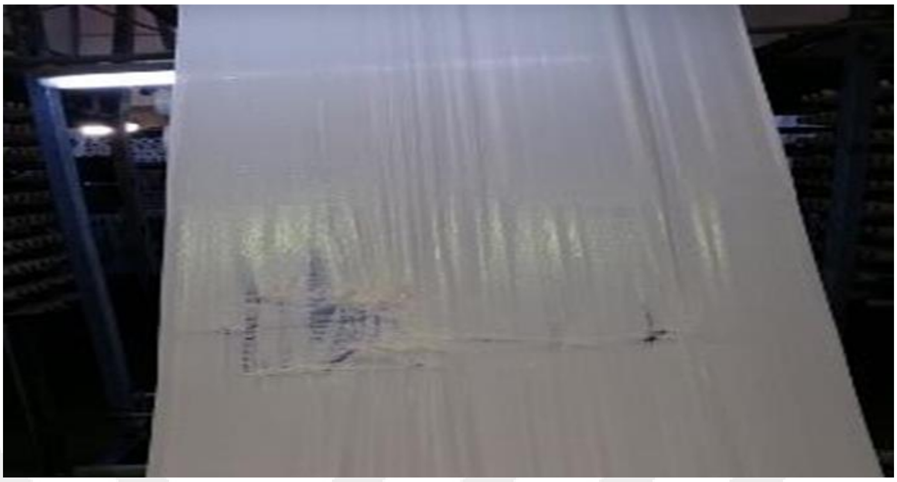


Figure 2.19 Broken Fabric

# 3. OVERVIEW OF METHODS

In this thesis, Discrete Fourier Transform DFT, Gabor filters and pixel classification have been used for fabric inspection and finding defects. Fast Region-based Convolutional Networks (Fast R-CNN) has been used for classification.

## 3.1. Fourier Transform

Fourier transform is a function or a tool that returns a wave or a signal's components that form it up. The Fourier transform proves that we re-write any waveform as a sum of sinusoidal forms. Fourier transform has been discovered by Joseph Fourier (1768 -1830). FT has been used in most fields; it has been used in engineering, physics, applied mathematics and even in chemistry. Lately, FT has been used in image processing which is considered an important tool because it decomposes an image into its sine and cosine components. Oil output in the Fourier transform is called Fourier or frequency domain, while the input which can be signal, waveform, image…. etc. called spatial domain as it's clear in figure 3.1.
Fourier Transform from the time domain to the frequency domain is given by 3.1:

$$F\{g(t)\} = G(f) = \int_{-\infty}^{+\infty} g(t)e^{-i2\pi ft}.dt \qquad (3.1)$$

Fourier Transform from the frequency domain to time domain is given by 3.2

$$F^{-1}\{g(f)\} = G(t) = \int_{-\infty}^{+\infty} G(f)e^{i2\pi ft}.df \qquad (3.2)$$

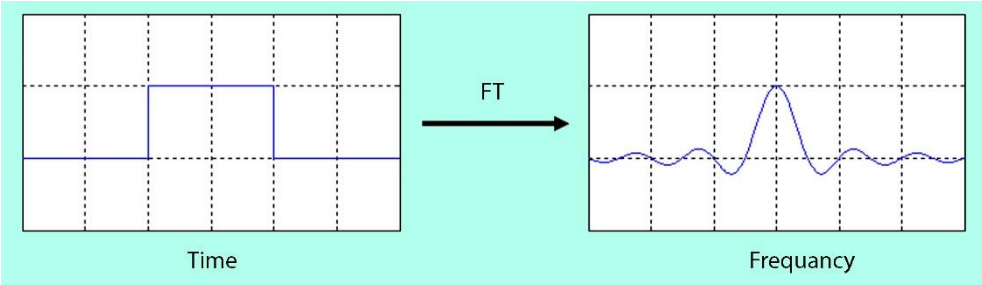


Figure 3.1 Fourier transform

### 3.1.1. Discrete Fourier Transform

Discrete Fourier Transform DFT or Discrete-time Fourier Transform DTFT is the equivalent of the FT for signals which have a finite sequence of data, i.e.: signals have data only at R instants separated by sample times T. Then we can write 2.1 as follows:

$$F\{g(t)\} = G(f) = \int_{-\infty}^{+\infty} g(t)e^{-i2\pi f t}.dt$$
$$= g|0|e^{-i0} + g|1|e^{-i\pi t} + \cdots + g|R-1|e^{-i\pi(R-1)t}$$

$$F\{g(t)\} = \sum_{k=1}^{R-1} g|k|e^{-i\omega kt}$$

Discrete Fourier transform can be written as 2.3:

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

The figure 3.2 shown below shows 3.2(a) which is considered to be one period of the periodic sequence in 3.2(b)

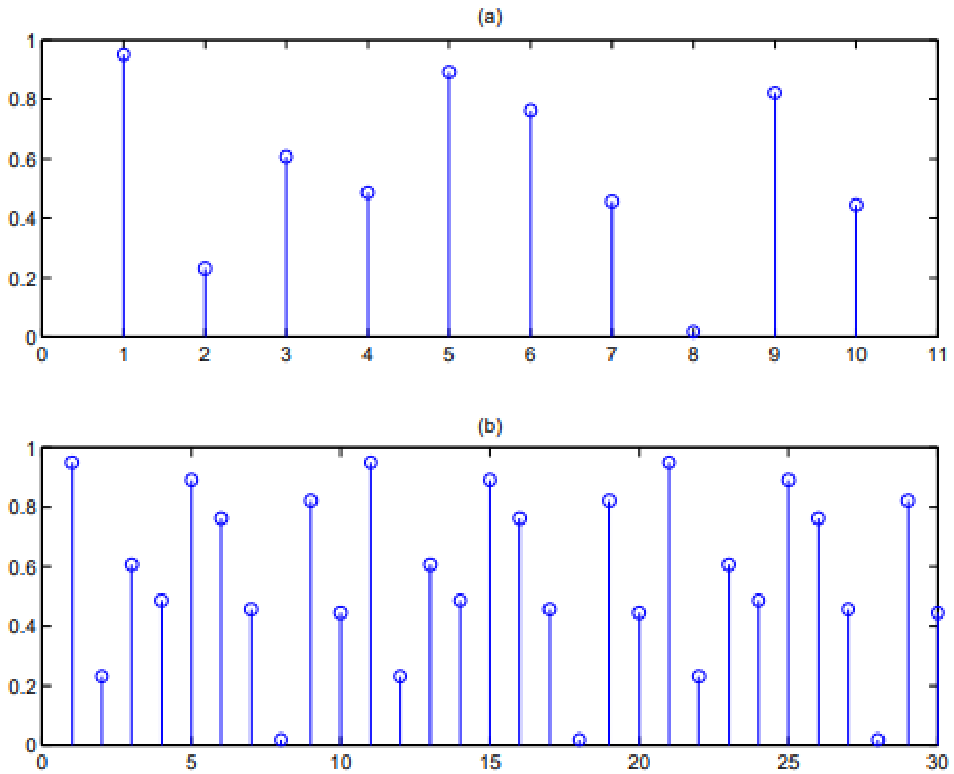



Figure 3.2: (a) sequence of R=10 sample. (b) DFT periodic implicit.

Inverse Discrete Fourier Transform IDFT is given by 3.4 as follows:

$$X_j = \frac{1}{\pi}\sum_{j=0}^{R-1} x_k e^{\frac{2\pi ijk}{R}} \tag{3.4}$$

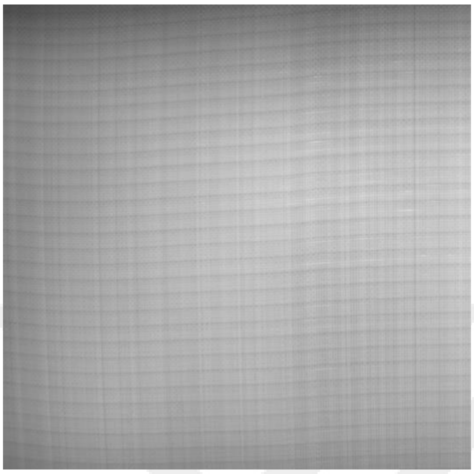
### 3.1.2. Fast Fourier Transform

Technology and science are developed in parallel, for example, digital signal processing or DSP. Nowadays everything is data, sometimes it's images from outer space, sometimes it's seismic vibrations…. etc. To make this data readable to human it needs to proceed. Computers use DSP to convert this data to its human readable version. Fourier transform is a reliable function in order to process these data, from time or space domain into the spectrum domain. time and frequency are alternative ways to represent these signals, while Fourier transform gives the relationship between these two representations. Discrete Fourier transform is like FFT but used to process the digital data. We call a faster and more efficient algorithm to calculate discrete Fourier transform, a Fast Fourier Transform (FFT).

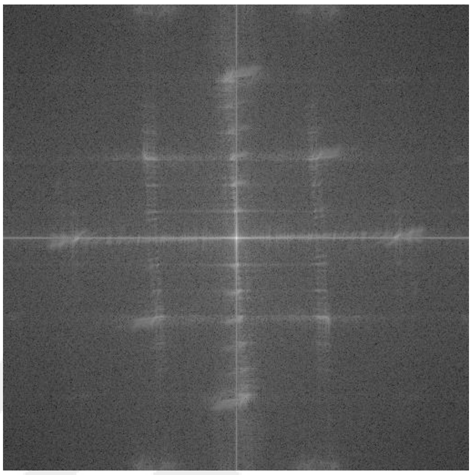
In this thesis, we are using fast Fourier transform to process images, while images have two dimensions so one-dimensional function like DFT is not suitable to be applied. Calculating the Fast Fourier Transform for each dimension of the input matrix equals to apply discrete Fourier transform with two dimensions MxN. 3.5 represents the image in the frequency domain after applying a two-dimensional Fourier transform is shown in 2.5 as follows:

$$f(p,q) = \sum_{n=0}^{N-1} \sum_{m=0}^{M-1} \mathrm{f(p,q)} e^{\frac{2\pi iqn}{N}} e^{\frac{j2\pi pm}{M}} \tag{3.5}$$

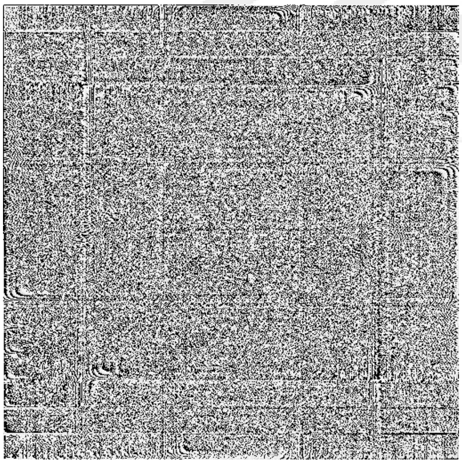
Applying Fourier transform to an image original fabric image is shown in 3.3(a) will produce a complex number valued output, the output can be represented by two images, the first one is magnitude shown in figure 3.3(b), the second one is the phase shown in figure 3.3(c). While the magnitude of the Fourier transform represents the important information of the geometric structure of the spatial domain image, it is the only needed in image processing. Nevertheless, the phase is used after applying some processing in the frequency domain, to apply the inverse Fourier transform and preserve both proceed magnitude and phase of Fourier image figure 3.3(d)



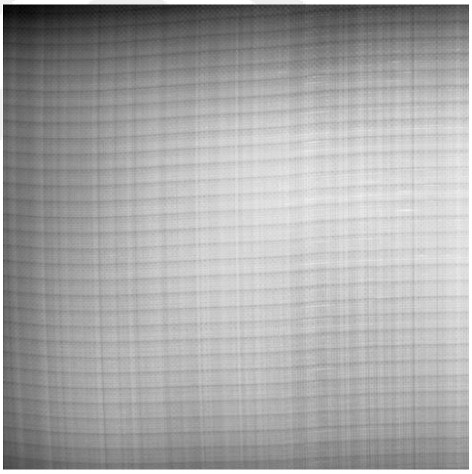
(a)Original Grayscale Image



(b) magnitude of Fourier transform



(c) phase of Fourier transform



(d) inverse of Fourier Transform

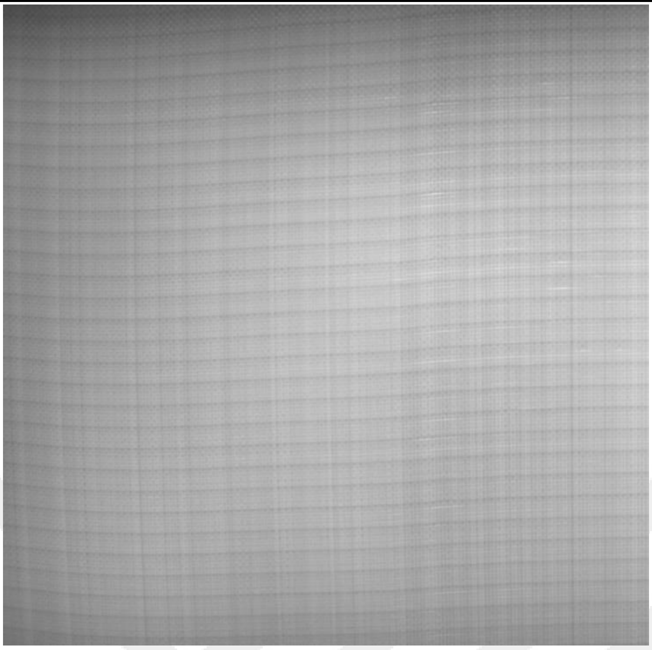
Figure 3.3: FFT, IFFT

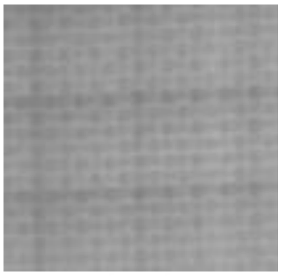
### 3.2. Normalized Cross-Correlation

Normalized Cross-Correlation or (NCC) is an efficient way to measure the similarity between two different time series to detect if there is a correlation between metrics with the same maximum and minimum values. Also, it is a reliable method to compute the similarity between two images. It is a more complicated technique for feature detection as well. When using this technique to compare two images, the main difference between normalized cross-correlation and the Ordinary Cross-Correlation (OCC), when using NCC it is less sensitive to linear changes in the amplitude of illumination between the two images. And the value of the threshold of NCC can be selected easier than the OCC threshold value. Therefore, NCC coefficients are bounded between the range of -1 and +1. Because of that, it has wide applications in image processing like pattern detection and recognition, motion analyzation, etc. NCC can be done using 3.6 as follows:

$$r = \frac{\sum_{(i,j)\in W} I_1(i,j).I_2(x+i,y+j)}{\sqrt{\sum_{i,j\in W} I_1^2(i,j).\sum_{i,j\in W} I_2^2(x+i,y+j)}} \tag{3.6}$$

In the figure 3.4 there are two images, figure 3.4(a) is the source image, with 1000x1000 dimension which has to be larger than the template image to make a meaningful normalization, and figure 3.4(b) in the template image with dimension of 100x100. Applying normalized cross-correlation to the fabric images in figure 3.4 results the surface in figure 3.5, where best-matched areas are indicated in peak values on the surface. Pixel indexes can be revealed as x and y plane by peak values of the result matrix. Therefore, using the NCC method let us demonstrate the best correlation between two images like in figure 3.6





(b)Tamplate image (100x100)

(a) Source Image ( 1000x1000)

Figure 3.4 Source and template Images

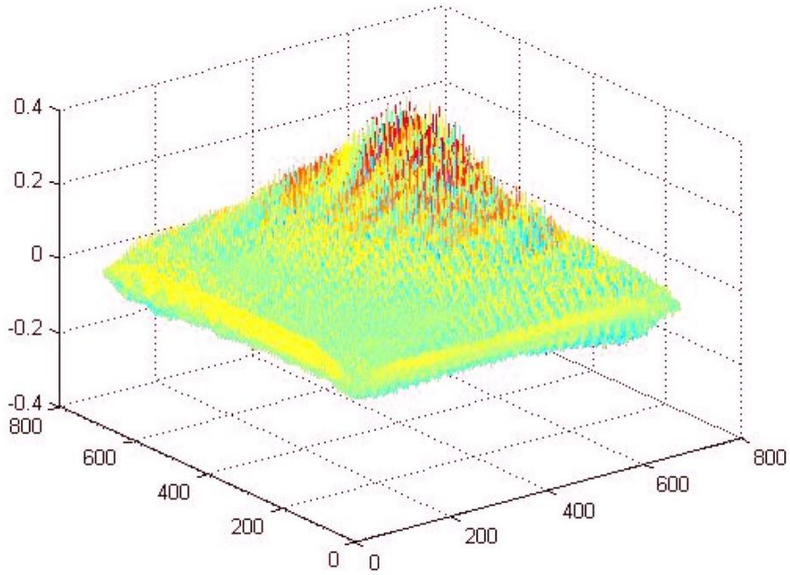



Figure 3.5 Normalized cross-correlation result

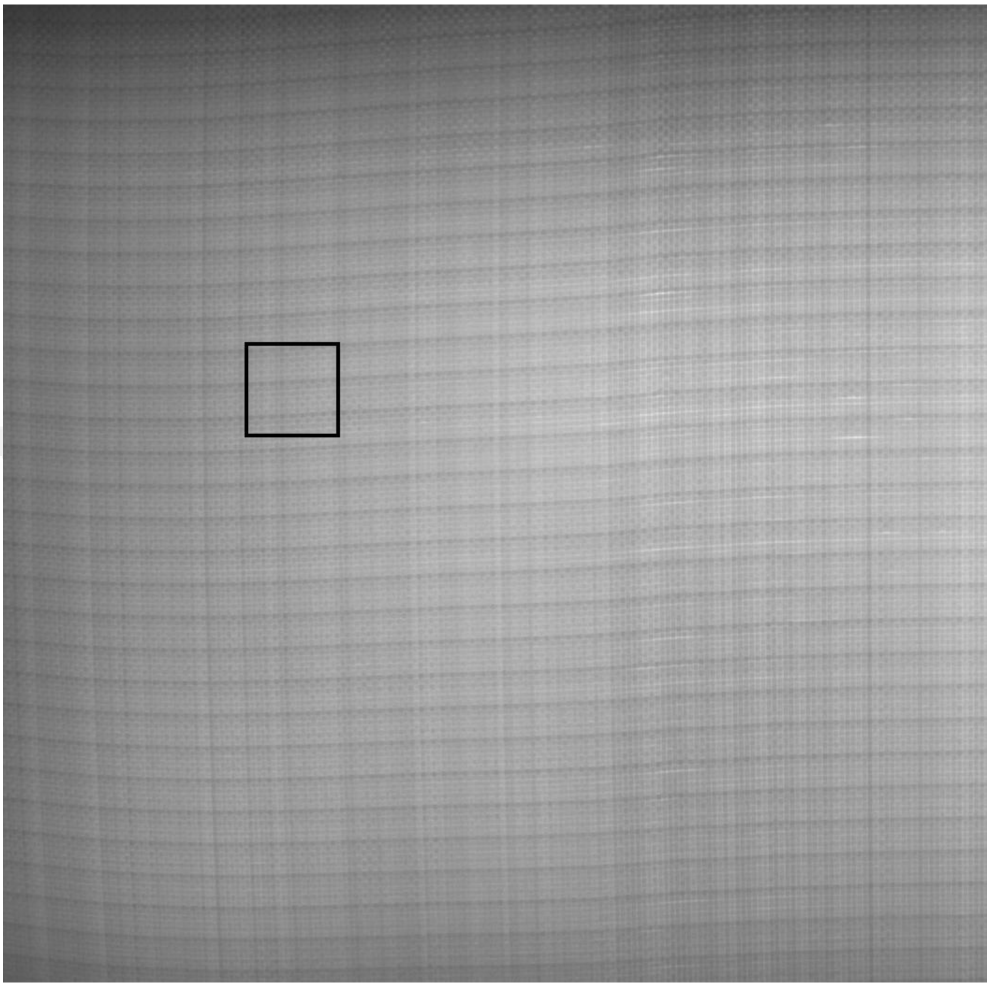


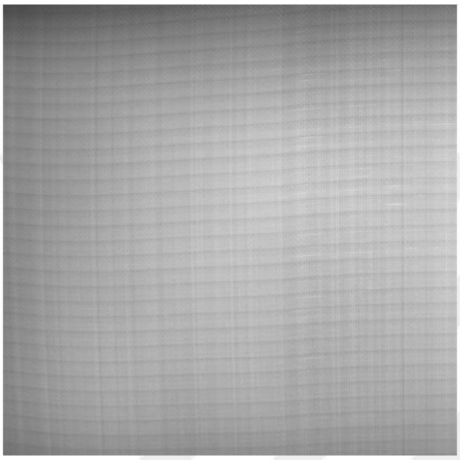
Figure 3.6 matched area on source image in figure 3.5

### 3.3. Histogram Equalization

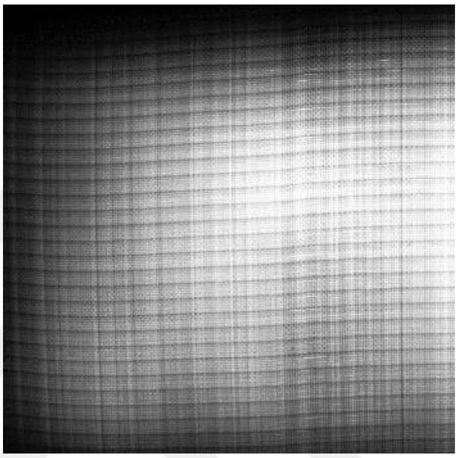
Histogram equalization is a technique used in image processing to make contrast enhancement by adjusting image intensities (Zhang and Bresee et al 1995). Histogram equalization can be utilized by reassigning grayscale values in the image pixels to obtain more uniform distribution. Histogram equalization can be made by using 3.7 as follows:

$$I_{i,j} = round((L-1)\sum_{n=0}^{i,j}\frac{number\ of\ pixels\ with\ intensity\ n}{total\ number\ of\ pixels} \qquad (3.7)$$

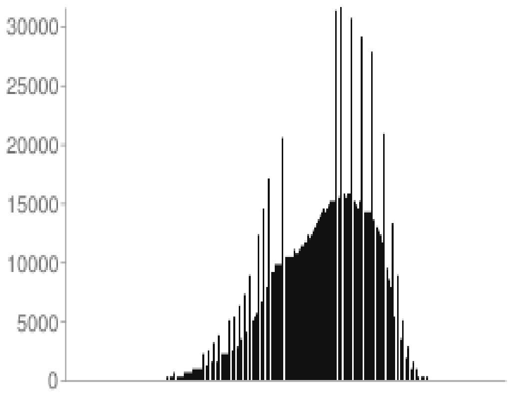
While L: the number of the possible intensity values.



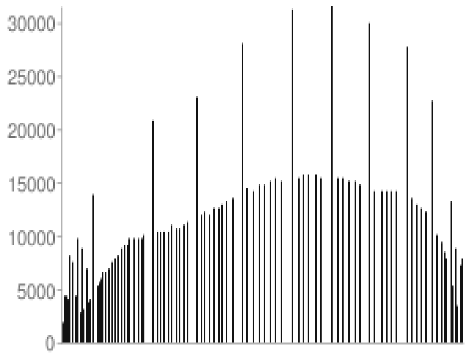
(a) Original Image



(b) Equalized Image




**(b)** Histogram Of Original Image




(c) Histogram Of Equalized image

Figure 3.7 Histogram Equalization Application

As in figure 3.7.a. the image has disorder in contrast, all the pixels have the value in the middle between the range of 75 and 200. Histogram equalization redistributes the pixels over all the grayscale range between 0 and 255.

### 3.4. Gabor Filter For Edge Detection

Gabor filter named after Dennis Gabor; it is a linear filter which has been used for many purposes. The most important use is texture analysis, i.e. it can analyze whether there is any specific content in the image and it is orientation-sensitive. In this thesis, the Gabor filter has been preferred to be used because of the following reasons:

- It corresponds in Fourier space to a blob on the logarithm of frequencies
- It has been used sufficiently as edge detector (K.R. Namuduri et al 1992).

Gabor filter odd component is given by 3.9 as follows:

$$s_0(x) = e^{-\frac{1}{2}\left(\frac{x}{\sigma}\right)^2} \sin(w_x x) \tag{3.7}$$

Gabor filter even component is given by 2.11 as follows:

$$s_e(x) = e^{-\frac{1}{2}\left(\frac{x}{\sigma}\right)^2} \cos(w_x x) \tag{3.8}$$

Gabor filter odd filter-based edge detector is given by 2.12 as follows:

$$S_0(x) * U(x) = \int_{-\infty}^{x} S_0(\varphi) d\varphi \tag{3.9}$$

Where $\varphi$ is the dummy variable of integration. Figure 3.8 shows an original fabric image, where figure 3.10 shows the image after applying Gabor filter, fabric edges are clear, this method helps us to locate the fabric edges and locate the hall defects in the fabric.

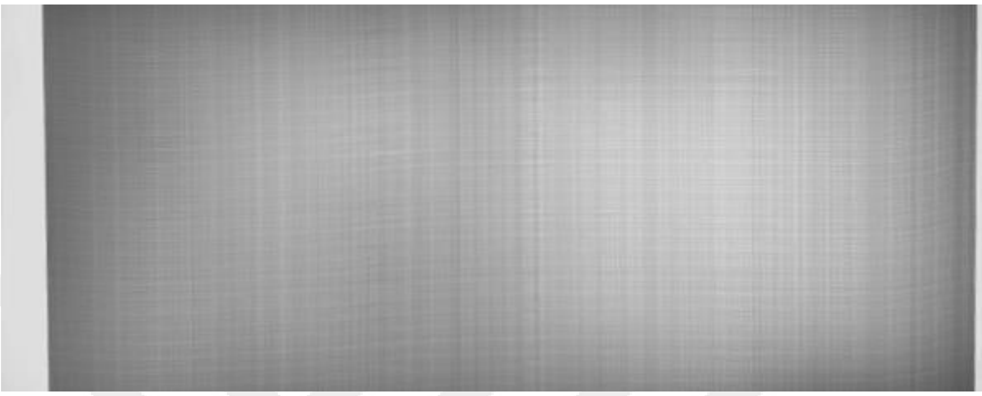


Figure 3.8 Original Image

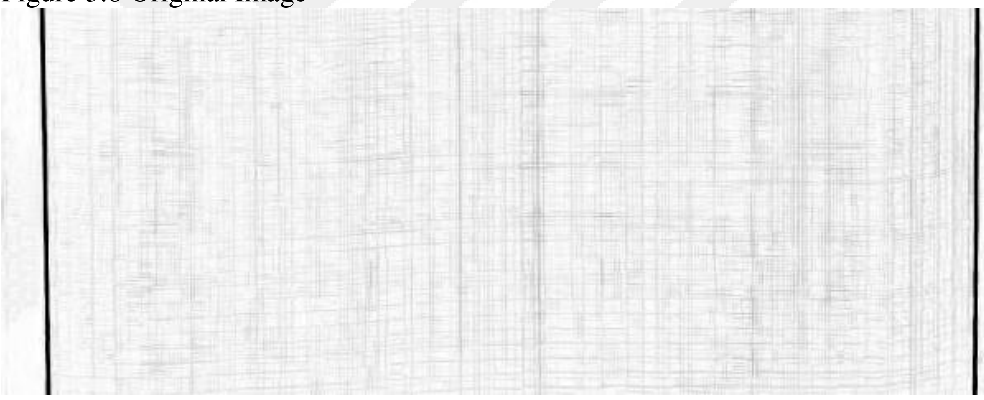


Figure 3.9 The Result Of Applying Gabor Filter To image In Figure 3.8

### 3.5. Faster R-CNN

In deep learning, the model has an input layer, hidden layers, and an output layer. The input layer takes in inputs and processes it in the hidden layers using weights that are adjusted during the training and give an output based on the trained data Figure 3.10. In this thesis deep learning is used in the defect classification, this section of the thesis is based on ( Shaoqing Ren et al 2016) Faster R-CNN.

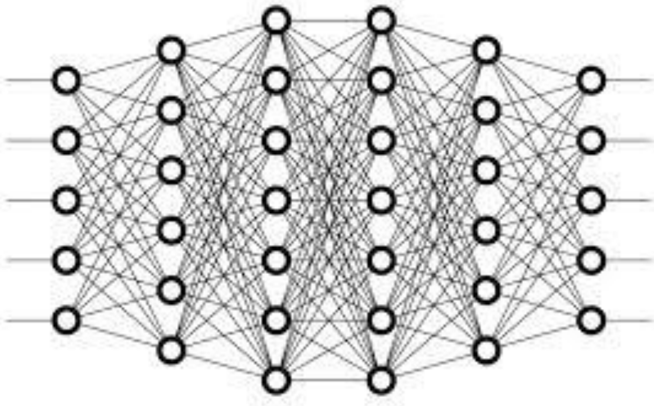


Figure 3.10. Deep Learning Layers

Faster R-CNN or Faster Region Proposal Network is the enhanced version of Fast R-CNN or Fast Region-based Conventional Network. Which is a deep learning model has been used to detect objects figure 3.11 shows Faster R-CNN real-time object detection.

In thesis, Faster R-CNN has been used as defect classification. The objective function following the multi-task loss in Fast R-CNN has been minimized. The loss function is given in 3.10 as follows:

$$L(\{p_i\},\{t_i\}) = \frac{1}{N_{cls}}\sum_i L_{cls}(p_i, p^*{}_i) + \beta \frac{1}{N_{reg}}\sum_i p^*{}_i L_{cls}(t_i, t_i^*) \qquad (3.10)$$

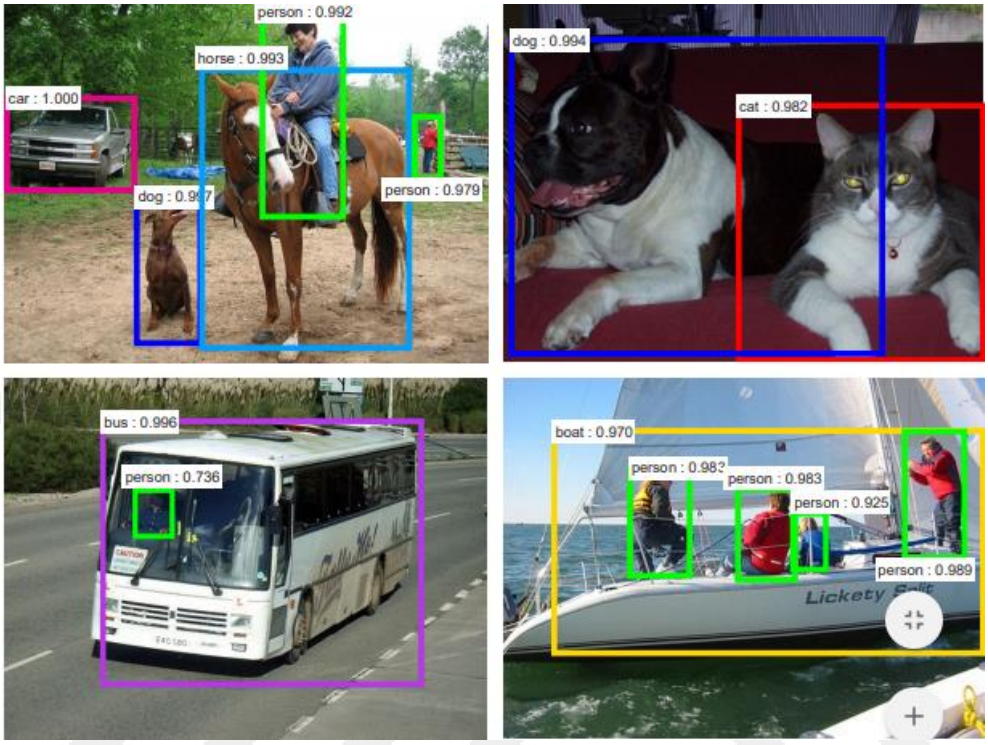



Figure 3.11 Faster R-CNN Real-Time Object Detection

# 4. DEVELOPMENT OF DETECTING AND CLASSIFICATION METHODS

## 4.1. Image Processing Model

Having defect detection with high accuracy is the goal alongside the less in the coast. generally, image processing functions need powerful hardware. In this part of the thesis, the curtailment of processes has been made without affecting the quality of the results.

There are two applications in this section. The first one is responsible for reading the encoder length data from PLC (figure 2.1) and capturing an image every 40 centimeters. Then stores it in the hard with the length data. The second application reads images from the destination file of the first application. Because of image processing can use the CPU and may cause the application to not respond to other processes, we used this method to avoid missing fabric. The capture application is running independently from the image processing application. Figure 4.1 represents the flowchart of image processing steps. First the application reads an image from the destination file of the other image-capture application, converts it to grayscale, applies the barrel distortion correction method, apply homogeneity equalization, apply Fast Fourier Transform, apply normalized cross-correlation, detect the edge to ensure that any found defect is inside the fabric area, apply subtraction, apply inverse FFT, apply another filter to calculate the, classify detected defect by image processing and give the decision. Then update the destination file’s links to check for newly captured images. If there are no captured images the application will be in the idle mode waiting for a new image. The application can work in real time as long as the PC has the ability to finish image processing functions before a new image to be captured. The defected images are stored in the hard drive after adding the proper caption.

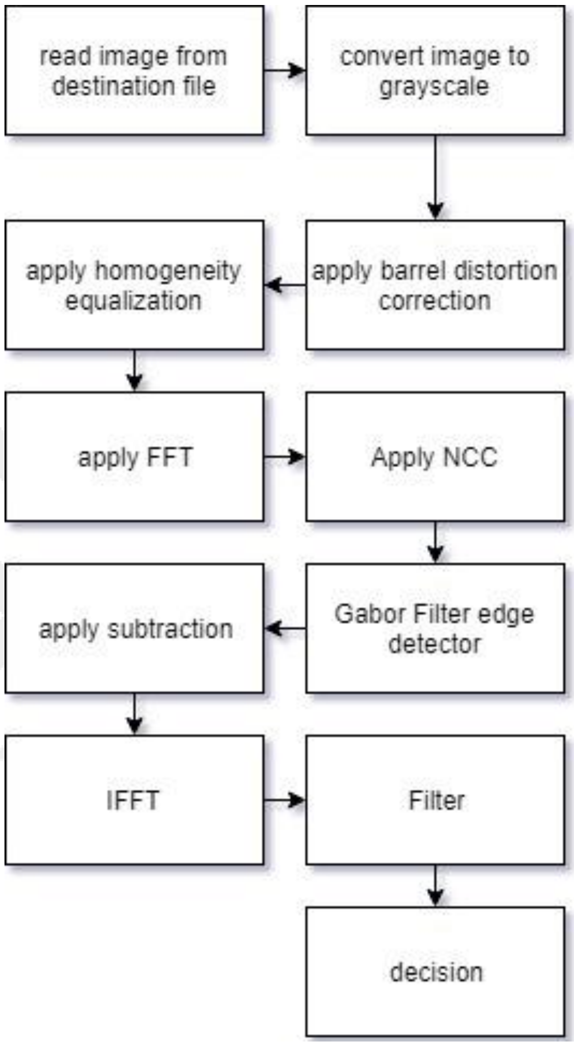



Figure 4.1 Flowchart of Image Processing steps

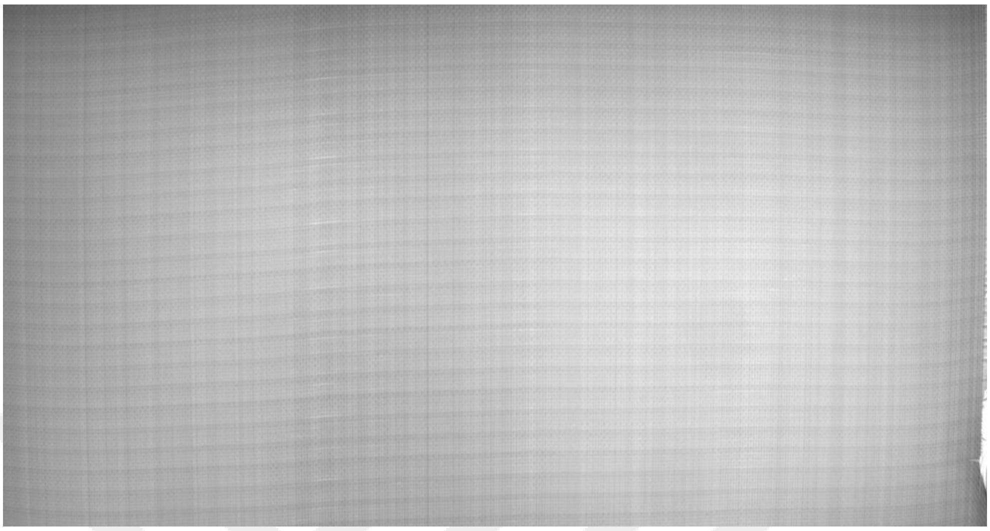
In this model, Homogeneity equalization has been proposed, and Barrel distortion correction has been used.

### 4.1.1. Homogeneity Equalization

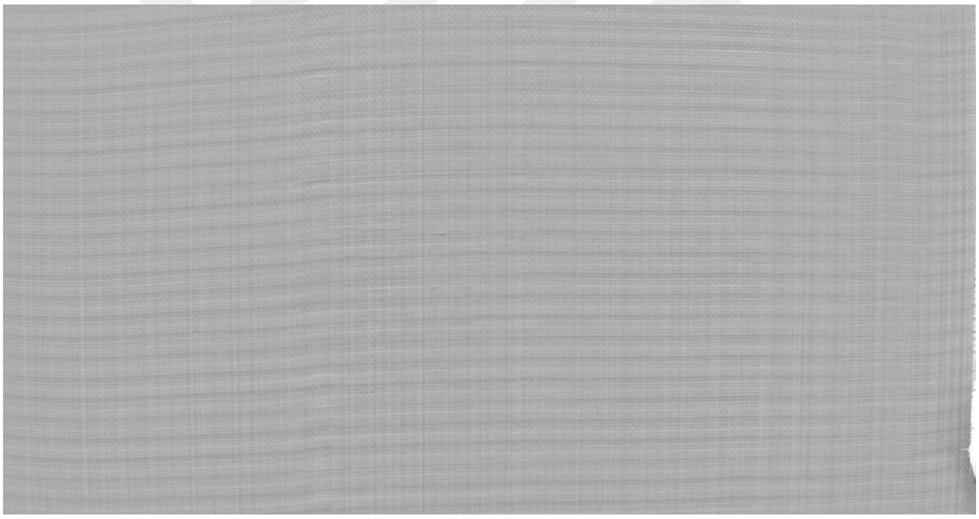
As it's clear in figure 3.7(a) the image is inhomogeneous, when facing this kind of issues in a precise job like inspecting defects using computer vision, can lead us to insufficient results. Most of the other theoretical studies relied on laboratory samples which have an approach with results limited the laboratory which is perfectly scanned with 100% homogeneity scale. While we are dealing with real machines in the factory, where lighting conditions would change from a captured image to another one. Histogram equalization can make it worse as it's clear in figure 3.7. In order to build a stable defect detection system, a homogeneity equalization has been developed. The goal of this equalization is to make the middle and the corners of the image's contrast homogeneous. The steps of Homogeneity Equalization are explained in figure 4.2 as follows:


Figure 4.2 the Flowchart of Homogeneity Equalization

This method can be useful alongside the other methods like FFT. The output of this method is explained in figure 4.3. (figure 4.3a) represents the inhomogeneous image with a defect on the right corner, while (figure 4.3b) represents homogeneity equalized image.



(a) Inhomogeneous image with defect in the right corner



(b) The original image after applying homogeneity equalization

Figure 4.3 Homogeneity equalization

### 4.1.2. Barrel Distortion Correction

Barrel Distortion or sometimes Lens Distortion is the natural result of using wide-angle lenses. In this thesis we used 8mm angled lens, therefore the images have barrel distortion. Barrel distortion can affect the fabric pattern in the images, which can lead to unwanted errors during other image processing methods. In order to get rid of the barrel distortion, we used barrel distortion correction (BDC) (Paul Bourke et al 2003). The Barrel Distortion Correction is calculated by 2.8 and 2.9 as follows:

$$P_x = \frac{P`_x}{1 - a_x||P/(1 - a_x||p||^2)||^2} \tag{4.1}$$

$$P_y = \frac{P`_y}{1 - a_y||P/(1 - a_y||p||^2)||^2} \tag{4.2}$$

While The "‖" notation indicates the modulus of a vector. Figure 4.4 shows an original fabric image, we can notice that the edges have a curved shape, while figure 4.5 shows the image after applying the barrel distortion correction method.

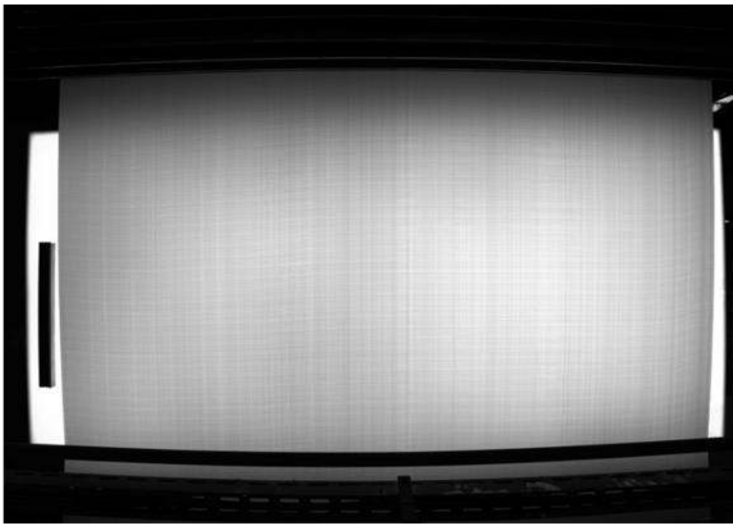


Figure 4.4 Original Fabric Image

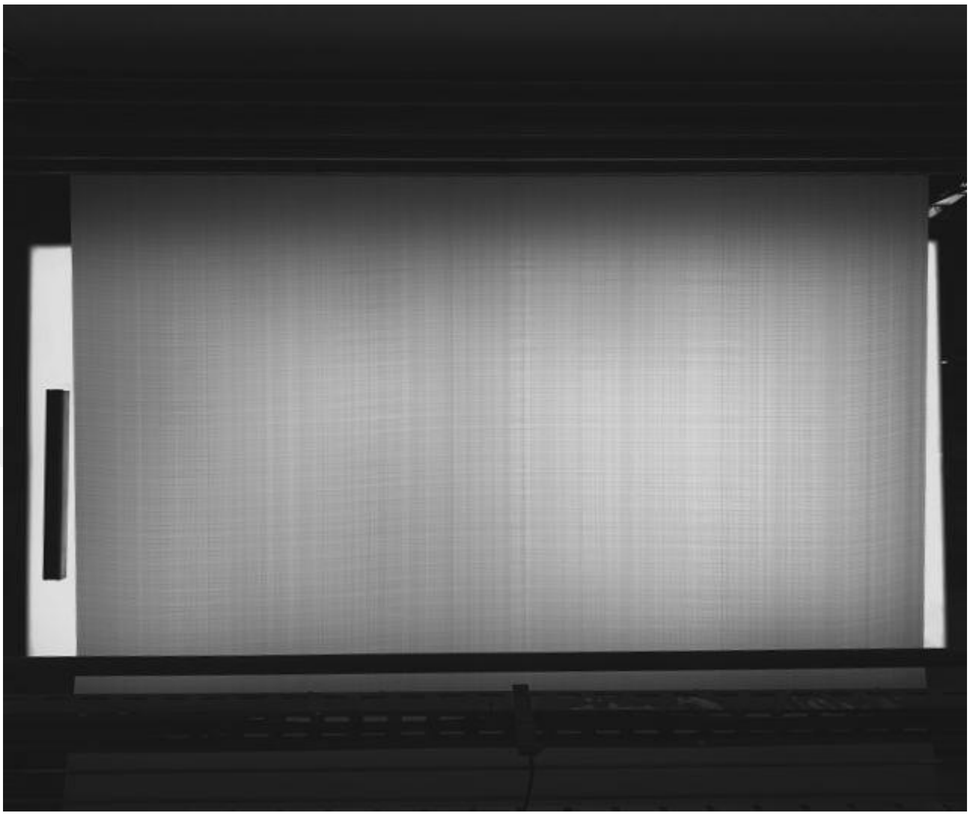


Figure 4.5 Original Image in Figure 4.4 After Barrel Distortion Correction

This method can improve detecting defects in the corners.

**4.2. Method Approach**

we are going to explain details about the tests we have made by using this methods step by step. Then we will evaluate the performance of the approach. As in table 2.1, we have a dataset contains 1100 sample. 100 of them are none- defected. Each kind of defects has 100 samples as we will list the test procedure, we made to confirm that our approach has the best results. Table 4.1 shows the first approach that explained in figure 4.5

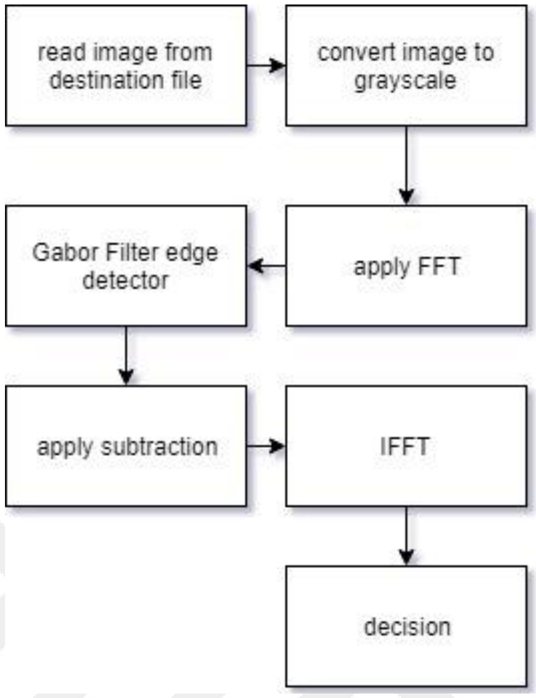
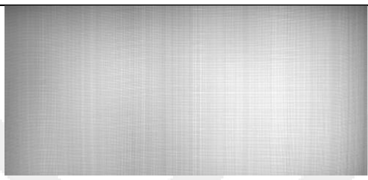
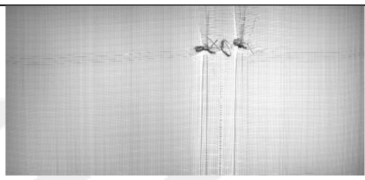
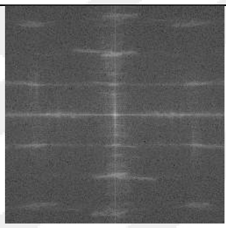
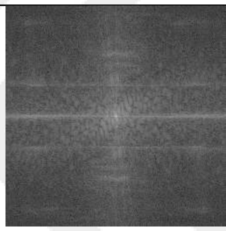
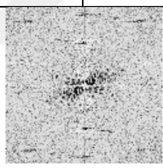
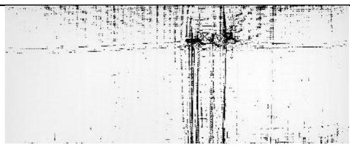



Figure 4.5 First Method approach

The results according to this approach were not satisfactory because of the following reasons:

- It’s proper for large and obvious defects like 5 or more centimeters, however, defects like missed yarn or weft haven’t been detected using this method. it couldn’t reveal more than 4% of this kind of errors.
- Using this approach, we can find almost 13% of defects in total.
- Some of the non-defected fabric images were counted as defected using this approach.

Table 4.1 step by step process of image processing first approach

| | Image | |
|---|---|---|
| | Reference | Defected |
| Image |  |  |
| Grayscale |  |  |
| FFT |  |  |
| Subtraction |  | |
| IFFT |  | |
| Result | The only remain pixels in black are defects according to this approach | |

The second approach is the enhancement of the first one, it's explained in the flowchart in figure 4.6 and processes' results are listed in table 4.2.

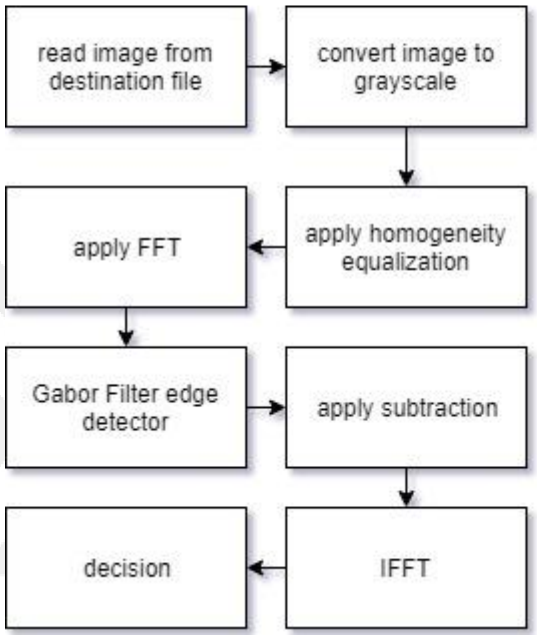


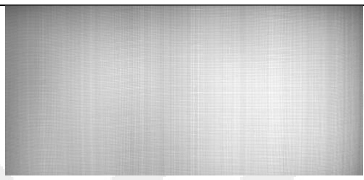
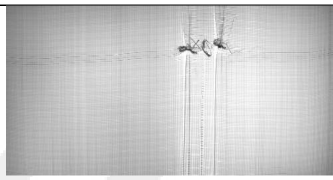
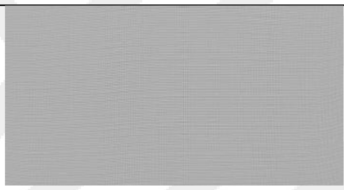
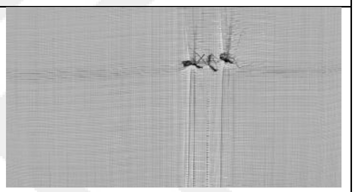
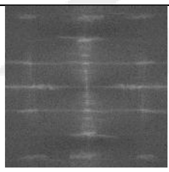
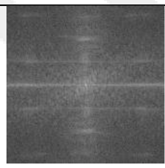
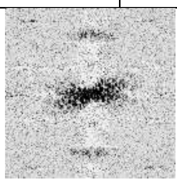
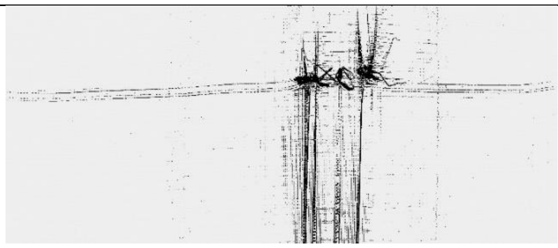

Figure 4.6 Second Approach

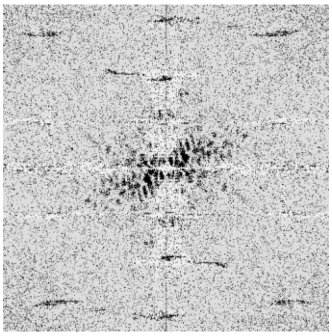
We can notice that results according to this approach are enhanced according to the previous approach. From figure 4.7 we can understand the following:

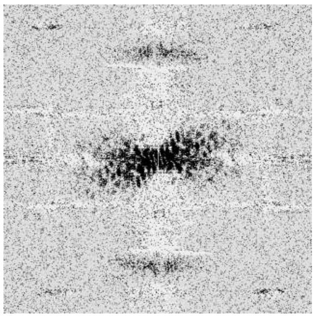
- most none-defected areas from the second approach result appear as defected in the first approach, that's a proof of method enhancement in locating the none-defected area (figure 4.7 (a) and (b)).
- The defected line (pointed with red arrows) in the first approach is discrete while it continues the line in the second approach, that's a proof of method enhancement in locating the defected areas (figure 4.7 (a) and (b)).

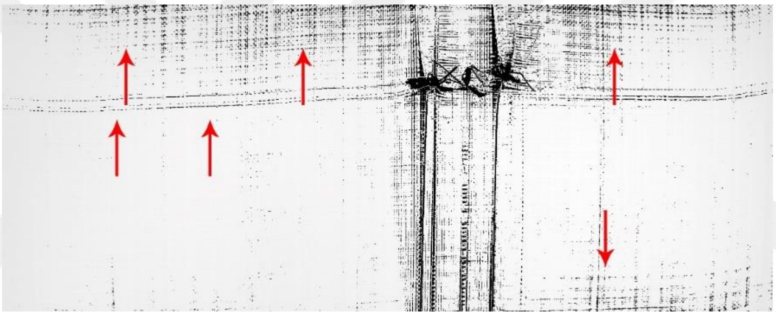
- The difference between Fourier transform subtraction from the first approach and the second approach is clear enough to predict that the result of the second approach is better than the first one.
- The second approach has found 74% of our dataset defects. It's better than the first one when comparing to 13%.
- Although the second approach's results are better than the first one is still not enough to detect the defects of less than 1 centimeter.

Table 4.2 second approach processes

| | Image | |
|---|---|---|
| | Reference | Defected |
| Image |  |  |
| Grayscale |  |  |
| Homogeneity equalization |  |  |
| FFT |  |  |
| Subtraction |  | |
| IFFT |  | |
| Result | The only remain pixels in black are defects according to this approach | |


(a)Subtraction of first approach FFT


(b)Subtraction of second approach FFT


(c)The found defects in the first approach (in black)

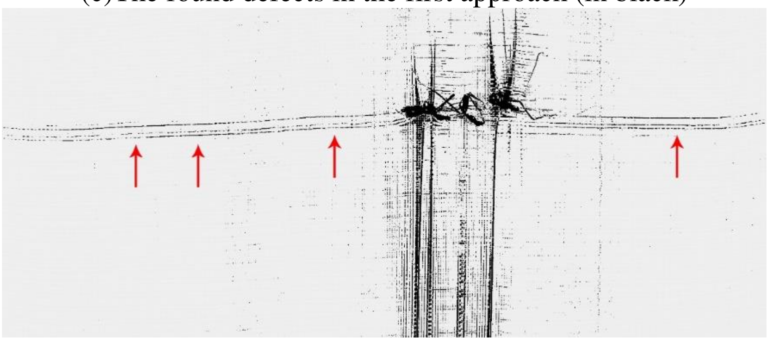
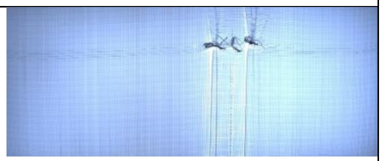
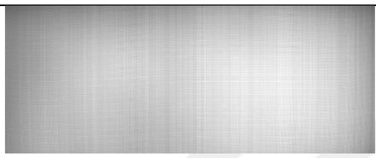
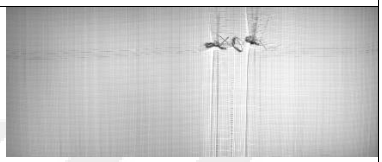
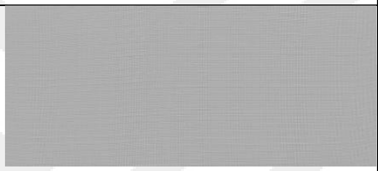
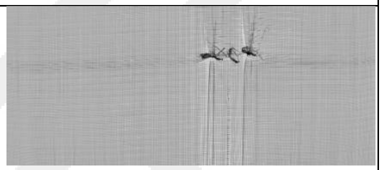
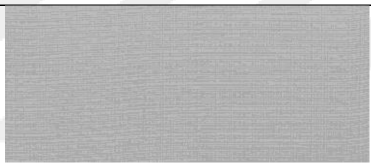
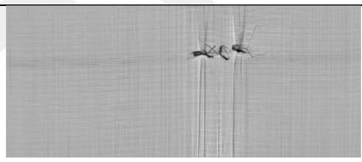
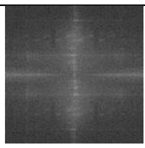
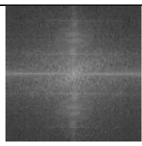
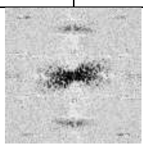
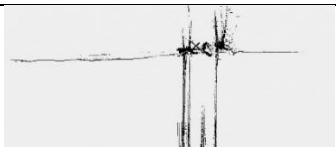

(d)The found defect in the second stage (in black)

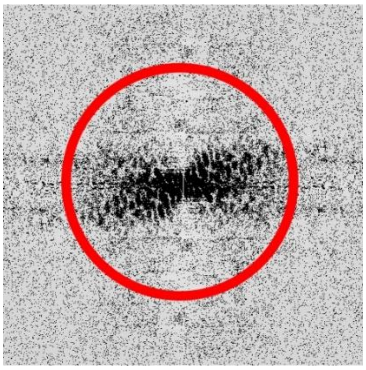
Figure 4.7 a comparison between the first approach and the second one

After too many changes and we got the final approach which we have mentioned before. Barrel distortion Correction, Normalized Cross-correlations, Gabor filters and width measurement methods have been used in the final approach. We can understand from the final approach's results by analyzing figure 4.8 following:

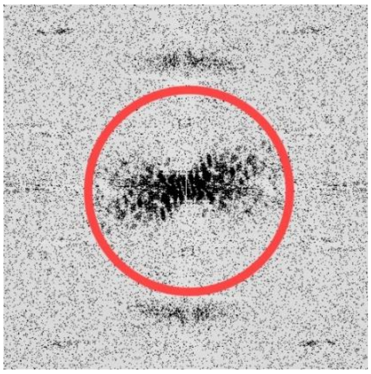
- Almost all none-defected areas have been evaluated correctly in the final approach, while some of them have evaluated as defected in the second approach. We can realize the enhancement between the second approach and the final approach from none-defected areas view-point.
- Almost all the defected areas have been evaluated correctly in the final approach, while some the defected areas have been evaluated as none-defected (figure 4.4 (c) and (d)).
- In the second approach's result (figure 4.7 (d)) has a free black pixel in none-defected area. These pixels are gone in the final approach as a result of using NCC and Barrel distortion correction.
- The difference between Fourier transform subtraction from the second approach and final approach is clear enough to predict that the result of the final approach is better than the second approach.
- The final approach has found 94.9% of our dataset defects. It's much better than 74% of the second approach
- Oil stains and machine part stuck defects classification using image processing has been developed and added to the final approach. 90.5% of these defect types have been classified correctly.
- Width length measurement filter has been added to the final approach. The output results of this filter are explained in table 4.3.

Table 4.3 final approach processes

| | Image | |
|---|---|---|
| | Reference | Defected |
| Image |  |  |
| Grayscale |  |  |
| Homogeneity equalization |  |  |
| Barrel DC |  |  |
| FFT |  |  |
| Subtraction |  | |
| IFFT |  | |
| Result | The only remain pixels in black are defects according to this approach | |

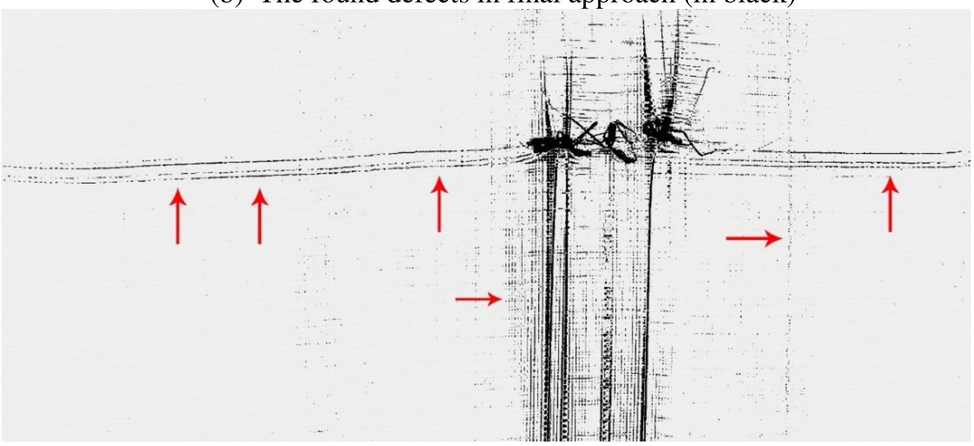


(a) Subtraction of final approach FFT



(b)Subtraction of second approach FFT

(b) The found defects in final approach (in black)



(c) The found defects in the second approach (in black)

Figure 4.8 a comparison between the second approach and the final one

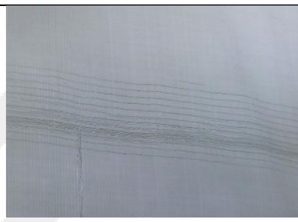
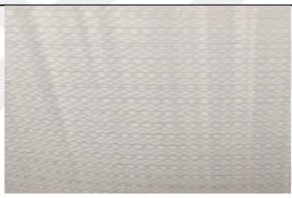
### 4.3. Defect classification Model

In this part, faster R-CNN has been used in cloud processing with Python. 170 defected images have been used for training with 25 non-defected images. The images were taken from the image processing application. Images have been classified into four classes, two class have been classified using image processing methods, these classes are classified as follows:

- Stain and machine part stuck (classified according to defect area pixels' color)
- Edge defect (classified according to defect position)

The other two classes are classified according to the reason that caused them as the table 4.4 shows.

Table 4.3 Classes of Faster R-CNN Model

| **Class 1** | | **Class 2** | |
|---|---|---|---|
| Node in fabric |  | Broken yarn |  |
| Broken fabric |  | Yarn overlap |  |
| Rarity in yarns |  | Broken warp |  |
| Machine Head Shifting |  | Using Different cord |  |
| | | folding |  |

# 5. RESULTS AND DISCUSSIONS

## 5.1 Approach of this Thesis

Using the data set in table 1.2. root mean square error (RMSE), mean absolute error (MAE) and mean absolute percentage error (MAPE) have been calculating using 4.1,4.2 and 4.2 as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y - Y')^2} \tag{5.1}$$

$$MAE = \frac{1}{n}\sum_{j=1}^{n}|y_j - \hat{y}_j| \tag{5.2}$$

$$MAPE = \frac{1}{n}\sum_{j=1}^{n}\frac{|Actual - result|}{|Actual|} \tag{5.2}$$

The application has been tested in the factory environment The results of the defect detection method are shown in Table 5.1 as follows:

Table 5.1. results of the methods

| | | Sample count | Counted as defected by methods | Counted as none-defected by methods | Percentage |
|---|---|---|---|---|---|
| | None-defected | 100 | 0 | 100 | 100,0% |
| | | | | | |
| **CLASS 1** | Node in fabric | 100 | 94 | 6 | 94,0% |
| | Broken fabric | 100 | 100 | 0 | 100,0% |
| | Rarity in yarn | 100 | 100 | 0 | 100,0% |
| | Machine head shifting | 100 | 100 | 0 | 100,0% |
| | Missed yarn | 100 | 99 | 1 | 99,0% |
| | | | | | |
| **CLASS 2** | broken yarn | 100 | 69 | 31 | 69,0% |
| | Yarn collapse | 100 | 100 | 0 | 100,0% |
| | Broken warp | 100 | 100 | 0 | 100,0% |
| | Missed warp | 100 | 100 | 0 | 100,0% |
| | Usage of different rope | 100 | 86 | 14 | 86,0% |
| | folding | 100 | 96 | 4 | 96,0% |
| | | | | | |
| | **Class1-2 total** | **1100** | **1044** | **56** | **94,9%** |

None-defected fabric images have been tested to ensure the accuracy of the methods. The detected errors have classified into four classes, two of them have been classified by image processing methods and the other two to use for deep learning training.

The dataset “width measurement test” has been used to measure the accuracy of the width measurement algorithm. 100 sample has been tested using the application the results are in table 5.2, RMSE, MAPE, and MAE are represented in table 5.3.

Table 5.2 edge width test for 100 sample

| No | The real width | Width by image processing | difference |
|---|---|---|---|
| 1 | 128.60 | 128.44 | -0.16 |
| 2 | 128.60 | 128.38 | -0.22 |
| 3 | 128.00 | 127.73 | -0.27 |
| 4 | 127.80 | 127.82 | 0.02 |
| 5 | 127.70 | 127.85 | 0.15 |
| 6 | 127.80 | 127.67 | -0.13 |
| 7 | 127.80 | 127.61 | -0.19 |
| 8 | 129.00 | 129.43 | 0.43 |
| 9 | 127.10 | 127.19 | 0.09 |
| 10 | 126.80 | 127.46 | 0.66 |
| 11 | 126.70 | 126.89 | 0.19 |
| 12 | 127.00 | 127.01 | 0.01 |
| 13 | 126.90 | 127.01 | 0.11 |
| 14 | 129.30 | 131.22 | 1.92 |
| 15 | 125.40 | 125.51 | 0.11 |
| 16 | 128.00 | 127.73 | -0.27 |
| 17 | 128.00 | 127.73 | -0.27 |
| 18 | 128.00 | 127.94 | -0.06 |
| 19 | 128.80 | 127.67 | -1.13 |
| 20 | 127.60 | 127.73 | 0.13 |
| 21 | 127.70 | 127.91 | 0.21 |
| 22 | 127.90 | 127.85 | -0.05 |
| 23 | 128.10 | 127.55 | -0.55 |
| 24 | 128.00 | 127.97 | -0.03 |
| 25 | 128.10 | 127.91 | -0.19 |
| 26 | 128.00 | 129.23 | 1.23 |
| 27 | 127.40 | 127.61 | 0.21 |
| 28 | 128.30 | 127.91 | -0.39 |
| 29 | 128.00 | 127.91 | -0.09 |
| 30 | 128.10 | 128.05 | -0.05 |
| 31 | 128.00 | 128.03 | 0.03 |
| 32 | 128.00 | 128.00 | 0.00 |
| 33 | 128.20 | 127.85 | -0.35 |
| 34 | 127.90 | 128.03 | 0.13 |
| 35 | 129.50 | 129.31 | -0.19 |
| 36 | 128.00 | 128.23 | 0.23 |
| 37 | 128.20 | 129.29 | 1.09 |
| 38 | 129.50 | 129.07 | -0.43 |
| 39 | 128.00 | 127.97 | -0.03 |
| 40 | 127.50 | 127.82 | 0.32 |
| 41 | 128.30 | 128.03 | -0.28 |
| 42 | 128.30 | 128.03 | -0.28 |

| | | | |
|---|---|---|---|
| 43 | 128.90 | 128.47 | -0.43 |
| 44 | 128.80 | 128.14 | -0.66 |
| 45 | 128.60 | 127.91 | -0.69 |
| 46 | 128.50 | 127.97 | -0.53 |
| 47 | 128.60 | 127.91 | -0.69 |
| 48 | 128.30 | 128.08 | -0.22 |
| 49 | 128.50 | 128.17 | -0.33 |
| 50 | 129.30 | 130.55 | 1.25 |
| 51 | 129.00 | 128.32 | -0.68 |
| 52 | 129.00 | 128.26 | -0.74 |
| 53 | 129.30 | 128.95 | -0.35 |
| 54 | 129.30 | 128.62 | -0.68 |
| 55 | 127.70 | 127.67 | -0.03 |
| 56 | 128.80 | 128.92 | 0.12 |
| 57 | 128.80 | 129.07 | 0.27 |
| 58 | 128.90 | 128.80 | -0.10 |
| 59 | 128.80 | 129.07 | 0.27 |
| 60 | 128.80 | 128.62 | -0.18 |
| 61 | 128.80 | 128.50 | -0.30 |
| 62 | 129.30 | 129.64 | 0.34 |
| 63 | 129.00 | 129.10 | 0.10 |
| 64 | 129.40 | 129.34 | -0.06 |
| 65 | 129.00 | 128.99 | -0.01 |
| 66 | 128.80 | 128.68 | -0.12 |
| 67 | 129.20 | 128.62 | -0.58 |
| 68 | 129.30 | 129.19 | -0.11 |
| 69 | 127.50 | 127.79 | 0.29 |
| 70 | 128.50 | 129.13 | 0.63 |
| 71 | 128.80 | 128.74 | -0.06 |
| 72 | 128.50 | 128.62 | 0.12 |
| 73 | 128.50 | 128.65 | 0.15 |
| 74 | 126.20 | 125.60 | -0.60 |
| 75 | 128.50 | 128.89 | 0.39 |
| 76 | 128.70 | 128.50 | -0.20 |
| 77 | 128.40 | 128.44 | 0.04 |
| 78 | 128.40 | 128.83 | 0.43 |
| 79 | 128.20 | 128.38 | 0.18 |
| 80 | 128.80 | 128.50 | -0.30 |
| 81 | 128.60 | 128.44 | -0.16 |
| 82 | 127.70 | 127.73 | 0.03 |
| 83 | 128.00 | 127.85 | -0.15 |
| 84 | 127.90 | 128.03 | 0.13 |
| 85 | 128.00 | 129.26 | 1.26 |
| 86 | 128.40 | 128.50 | 0.10 |
| 87 | 128.80 | 129.46 | 0.66 |

| | | | |
|---|---|---|---|
| 88 | 129.00 | 129.55 | 0.55 |
| 89 | 128.90 | 129.16 | 0.26 |
| 90 | 128.70 | 129.10 | 0.40 |
| 91 | 129.00 | 129.31 | 0.31 |
| 92 | 128.80 | 128.98 | 0.18 |
| 93 | 129.10 | 129.25 | 0.15 |
| 94 | 129.00 | 128.98 | -0.02 |
| 95 | 129.00 | 129.04 | 0.04 |
| 96 | 129.00 | 129.55 | 0.55 |
| 97 | 128.90 | 129.04 | 0.14 |
| 98 | 129.00 | 129.16 | 0.16 |
| 99 | 128.90 | 129.16 | 0.26 |
| 100 | 129.00 | 129.22 | 0.22 |
| Sum | | | 2.67 |

The MRSE, MAE, and MAPE are shown in table 5.3 as follows:

Table 5.3 The RMSE, MAE, and MAPE of the width measurement algorithm

| MRSE | MAE | MAPE |
|---|---|---|
| 0.45421 | 0.3186153079 | 0.002479222873 |

Machine part stuck alongside oil stain defects have been classified using image processing methods, table 5.4 shows the results as follows:

Table 5.4 oil stain and machine part stuck defect classification by image processing

Table 5.4 Shows the results of this approach

| | Sample count | Counted as defected by methods |
|---|---|---|
| Oil stain | 100 | 81 |
| Machine part stuck | 100 | 100 |
| | | |

Table 5.5. Faster R-CNN Model Results

| Class | Count | Classified Correctly | Classified Falsely | percentage |
|---|---|---|---|---|
| 1 | 35 | 23 | 12 | 65% |
| 2 | 35 | 22 | 13 | 62% |

The RMSE, MAE, and MAPE for Faster R-CNN Approach shown in table 5.6 as follows:

Table 5.6 RMSE, MAE and MAPE for Faster R-CNN Approach

| RMSE | MAE | MAPE |
|---|---|---|
| 12.5 | 12.5 | 0.35 |

**5.2 Discussions**

**5.2.1 Overall Discussion on image processing results**

The results obtained in this study are the reveal that the methods we used in image processing gave a sufficient result. While the Faster R-CNN model gave insufficient one.

we will look to the similar researches' result and compare it with this thesis.

As in table 1.2, we have a dataset contains 1100 sample. 100 of them are none-defected. Each kind of defects has 100 samples as we will list the test procedure, we made to confirm that our approach has the best results. In the previous chapter, we presented the results of the first two approaches, then we compared it with the final approach. We can confirm on these points in our final approach:

- Almost all none-defected areas have been evaluated correctly in the final approach, while some of them have evaluated as defected in the second approach. We can realize the enhancement between the second approach and the final approach from none-defected areas view-point.
- Almost all the defected areas have been evaluated correctly in the final approach, while some the defected areas have been evaluated as none-defected (figure 4.4 (c) and (d)).
- In the second approach's result (figure 4.7 (d)) has a free black pixel in none-defected area. These pixels are gone in the final approach as a result of using NCC and Barrel distortion correction.
- The difference between Fourier transform subtraction from the second approach and final approach is clear enough to predict that the result of the final approach is better than the second approach.
- The final approach has found 94.9% of our dataset defects. It's much better than 74% of the second approach
- Oil stains and machine part stuck defects classification using image processing has been developed and added to the final approach. 90.5% of these defect types have been classified correctly.
- Width length measurement filter has been added to the final approach. The output results of this filter are explained in table 4.3.

The final approach has a disadvantage of the cost. A large number of processes have to be made for each image comparing to the second approach. But it's necessary in order to get rational results.

### 5.2.2 Overall Discussion on defect classification using deep learning

In this thesis, we have focused on the image processing section because it's the most important during the production. Faster R-CNN model has been used for classification where it was made on purpose of detecting objects such as (human, animal, pot, food, etc.). using this model proved that it gives insufficient results.

### 5.2.3 Comparing This Study with Other Studies

In order to figure out the efficacy of this study, we have compared it to the other studies, especially with the ones which have the same methods in common. As I explained before most of the other studies have been made under laboratory conditions. Some of the studies used a dataset was collected from a real factory. We will highlight a study was made by (NuriGökay Titrek 2016) because it had some methods in common with ours. A dataset contains 262 samples have been collected from a real fabric factory. 56 of the samples are none-defected. While 206 samples have defects with 14 types of defects.

FFT and NCC have been used in Titrek's study. He claimed that his methods found 71% of the samples with defects. The result of his study is shown in table 5.7

Table 5.7 (NuriGökay Titrek 20016) 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% |

Analyzing the results (table 5.7 NuriGökay Titrek) we can highlight the following points:

- His dataset is not enough, for example, the “tear”, “thick end” and “double end” defects have only two samples for each one. Most of the other defect samples are less than 10. This can make an unstable result. Our results are reinforced with 100 samples for each type of defect in our dataset. Which can give a more stable result.
- the found defects using his method is 71% of the total defected samples. While our approach has found 94.9% of the total defects.

- His dataset was scanned using a linear scanner. While our dataset was collected using an area scan camera, his dataset is homogenous already, manually cropped and doesn't have any barrel distortion unlike ours. So, when comparing the methods one to one we should include only defect inspection method and exclude the enhancement methods which is impossible in our situation because our datasets have been collected in different conditions

- His study doesn't include a none-defected analyzation. So we can't compare the none-defected samples fault detection with our approach.
- The other method doesn't have a classification feature to compare it with ours.

Comparing with the other studies:

- Defect classification by image processing couldn't be compared to other methods because there wasn't any related study with common methods or dataset.
- Defect classification by deep learning couldn't be compared with other studies uses the same model because all the other Faster-R-CNN models were built to recognize objects, not defects.
- (Yundong Li et al 2017) used Fisher Criterion-Based Deep Learning for inspecting defects and classify it in one model, they claimed that they got a rational result, but the dataset that they used was generated using a dataset generator. Because of that, we can't ensure the resulting stability with real dataset samples.
- None of the other researches has the real-time running feature, because none of them used a camera to instantly capture-process. Generally, the

datasets are prepared previously. While our results based on a real-time capture-process feature (except classification using deep learning).

# 6. CONCLUSION

Technology evolution is increasing day by day. It has many innovations in textile word. Therefore, the traditional ways of inspecting textile disable enhancing textile both production quality and speed. The aim of this study is to create a standalone system to inspect and detect the quality control in fabric factory, this system will replace the manned based quality control system. The reasons of building this system are to improve the quality control accuracy which is the reason of producing fabric with better quality that meets the customer needs in first place, and to minimize the cost of production procedure while automating the quality control will replace the manned control system and reduce the workers number. In literature review we have reviewed the related researches, benefit from their experiments and get a start point. Fabrics have periodic patterns in general, for this reason, we found that Fourier transform is a very efficient approach for fault inspection and detection. Nevertheless, the FT features are basic, in other words, they don't determine nether the location of the defect nor its type. Because of the FT bases has an infinite length, it would be an expensive process to quantify the contribution from each component of the spectral. Generally, FT based systems use neural networks to get the mentioned features. Actually, there is no need to use neural network always to get these features. Some of the studies developed a fabric identifier by using Local Fourier Transform LFT. We found in the literature review that there is no common standard data set for comparison between these approaches. Some studies based on FT but they weren't tested sufficiently, the others' claimed as successful despite of the unknown reliability. Some of the studies had the data set in common so they had the chance to compare and analyze each other's approaches. In this research, we have created a system that inspects all the apparent defects alongside almost all the tiny defects with rational efficacy results which cannot be done with a manned quality control system. First we started from choosing the camera, the weaving machine we used Starlinger Alpha 6.0 has the production width of 128 centimeters on average, the used cord is between 1-6 millimeter. Defects of the 2-millimeter range have to be detected. Then a 2 millimeter has to be presented at least by 3 pixels. According to this calculation, the captured image needs to be digitally represented by at least 2250 pixels. The same for length a square area has to be captured, then the camera resolution has to be at least 2250x2250 =5 megapixel. One other factor is the connection interface, while one BMP formatted image has to be captured and transferred to PC in less than 2 seconds, then the connection between camera and PC has to be 10 megabytes per second at least. Another factor is exposure minimum time, as a definition, exposure time is the shutter speed and aperture, while we are dealing with moving object, exposure time is very important because it can affect the image quality. In other words, if exposure time longer, then the shutter is slower, so the camera's sensors are being affected with more light, the image will have more blur. In image processing, when inspecting defects on a moving fabric surface, we don't want to miss any detail. That's why exposure time is really an important factor. Cameras with faster shutter are more expensive in general, we need to identify the camera minimum properties in order to choose the perfect camera that can do the job without any extra costs. Estimating the camera sensor maximum exposure time using environment variables like sensor resolution, we have calculated the maximum exposure time for the wanted camera which is 2 milliseconds. We focused on defect detection and gave it more priority than defect classification. Because detecting defects is the main problem in the quality control department, while defect classification had less interest. We used a modified version Fourier Transform in image processing mainly to fit our purposes. In digital signal processing or DSP, while Nowadays everything is data, sometimes it's images from outer space, sometimes it's seismic vibrations…. etc. to make this data readable to human it needs to proceed. Computers use DSP to convert this data to its human readable version. Fourier transform is a reliable function in order to process these data, from time or space domain into the spectrum domain. time and frequency are alternative ways to represent these signals, while Fourier transform gives the relationship between these two representations. Discrete Fourier transform is like FF but used to process the digital data. We call a faster and more efficient algorithm to calculate discrete Fourier transform, a Fast Fourier Transform (FFT). While images have two dimensions so one-dimensional function like DFT is not suitable to be applied. Calculating the Fast Fourier Transform for each dimension of the input matrix equals to apply discrete Fourier transform with two dimensions MxN. We used Gabor filters for edge detection which is a linear filter. The most important use is texture analysis, i.e. it can analyze whether there is any specific content in the image and it is orientation-sensitive.

When we made our approach the results weren't insufficient because of inhomogeneous in images, when facing this kind of issues in a precise job like inspecting defects using computer vision, can lead us to insufficient results. Most of the other theoretical studies relied on laboratory samples which have an approach with results limited the laboratory which is perfectly scanned with 100% homogeneity scale. While we are dealing with real machines in the factory, where lighting conditions would change from a captured image to another one. Histogram equalization can make it worse. In order to build a stable defect detection system, a homogeneity equalization has been developed. The goal of this equalization is to make the middle and the corners of the image's contrast homogeneous. Having defect detection with high accuracy is the goal alongside the less in the coast. generally, image processing functions need powerful hardware. In this part of the thesis, the curtailment of processes has been made without affecting the quality of the results.

We have developed two applications working synchronously. The first one is responsible for reading the encoder length data from PLC, and capturing an image every 40 centimeters. Then stores it in the hard with the length data. The second application reads images from the destination file of the first application. Because of image processing can use the CPU and may cause the application to not respond to other processes, we used this method to avoid missing fabric. The capture application is running independently from the image processing application. First the application reads an image from the destination file of the other image-capture application, converts it to grayscale, applies the barrel distortion correction method, apply homogeneity equalization, apply Fast Fourier Transform, apply normalized cross-correlation, detect the edge to ensure that any found defect is inside the fabric area, apply subtraction, apply inverse FFT, apply another filter to calculate the width, classify detected defect by image processing and give the decision. Then update the destination file's links to check for newly captured images. If there are no captured images the application will be in the idle mode waiting for a new image. The application can work in real time as long as the PC has the ability to finish image processing functions before a new image to be captured. The defected images are stored in the hard drive after adding the proper caption.

When we used the image processing methods and algorithms the first time, we had insufficient results. We kept working on enhancing the first approach to get better results. We developed a filter to make width measurement, which has an importance in quality control. The width should be between certain ranges of values; too wide or narrow fabric can cause another defect. Furthermore, it is unwanted according to the customers' aspirations. Our dataset had 1100 sample, which is captured using an area scan camera from the production line from Abdioğulları Plastic and Packaging Industry Co. One hundred samples for each type including width measurement and none-defected samples. Our approach detected 94.9% of the detected samples. Obtained 90.5% correct classification of "oil stains" and "machine part stuck" defects using image-processing methods, which can be considered as efficient. Obtained 63.5% defect classification using deep learning method (Faster R-CNN) which can be considered as an inefficient result. In future studies, we intend to enhance classification efficacy.

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## CURRICULUM VITAE

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