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An Automated System for Fabric Faults Inspection to Enhance Textile Handicrafts

Team Work

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(2013)

Summary:

The conventional inspection process in the weaving mills usually depends on human visual inspection. The human visual inspection process only detects 60 to 70% out of the total fabric defects [1] while the residual defects pass without detection. This causes several problems in the following processes of manufacturing. In addition, fixing defects is a complicated process and mostly the defective parts are discarded as waste that might be recycled or sold at low price (usually 45 to 65% from the free defect price) [2]. This project introduces an automated system to detect and classify woven fabric defects replacing the conventional inspection process.

Our proposed system utilizes a digital camera to acquire and transmit fabric images to a computer which enhances and extracts the features for each image. Then, the features are processed using Artificial Intelligence technique to detect and classify the fabric defects. Also, this automated system will be able to predict the sources of the defects to be fixed. These defects will be recorded in a database providing a report including the frequent defects to fix their sources and consequently increasing the quality of the manufactured fabrics. Applying such automatic system in weaving mills will increase the profit and the product quality.

This automated fabric inspection system is independent of the human's experience. This will increase the efficiency of the inspection process through detecting very

small defects that are difficult to be detected by the labor. Moreover, the automated fabric inspection system will not get bored or tired like the labor through the long time of inspection process. Researchers tried to apply automatic inspection procedures in many ways [2-6] but these ways introduced mainly methods to analyze the images without a complete system that connected to the computer.

Contents:

List of tables:

List of figures:

CHAPTER 1

INTRODUCTION

Chapter 1

Introduction

The main problem in Textile Industry is to increase the ratio between Quality and Productivity with high flexibility and minimization of the cost. So it is so important to test the products to ensure quality. Most of textile testing requires a subjective evaluation by trained personnel. But this person cannot work 24 Hours with zero faults, so the mill must have a lot of trained persons for these evaluations. Also subjective evaluation yield erratic results and costs a lot of money. So it is important to have on-line and high speed quality controls to enable automation to improve quality value, in addition to increase of production speeds.

Image processing technique was rapidly developed for inspection of various materials and ensures quality, and a lot of cameras manufactures offered computerized cameras with high options like: speed, accuracy, and optical zooming to make achieved success process. Image-processing techniques included operations performed by computer in order to carry out pre-programmed tasks and many people called this (machine-vision system). These techniques analyze 2-D or 3-D Dimensional scenes to extract important information (features) and take decisions as to pre-define inputs. Like human-vision system self-programming that acquired knowledge by trial and error, computer vision needs programming for each task. Image processing enhances the quality of images by mathematical functions to make easy analysis and make calculation for getting numerical results to take decision. Other approach is to divide continuous video to individual digital scenes and track objects which are different from the surroundings by separating the object from their back ground and compute its blob measurements and location.

For making a success computer vision system it is important to understand optics theory, image principles, image environment, image formation, image types, texture features and deal with image accessories like cameras. Digital image-processing means self computer-processing of the picture or images in numerical form. Image processing needs large numbers of steps depend on the nature of the image. Some of processing steps involve: feature enhancement, image segmentation, image-smoothing, image-sharpening, image restoration, image addition, subtraction, and multiplication, image-filtering, image compression, image transformation, image classification, and finally image analysis. Enhance the quality of the image is important to make better analysis.

Simple form:

(1) Acquisition, (2) Storage,

(3) Processing, (4) Results,

(5) Decision.

1.1. Digital Images Fundamentals

1.1.1. Image

The digital form of an image is a 2-D Matrix where each element of the matrix contains a value represents the intensity of light of this pixel.

1.1.2. Image Locations

1.1.2.1. Pixel Indices

For expressing locations in an image you may use pixel indices which are integer values range from 1 to the size of the image (discrete indices).

1.1.2.2. Spatial Coordinates

Second method to express image location (continuously coordinates), location in an image are positions on a plane, and represented by x and y (not row and column as in the pixel indexing system).

1.1.3. Image Types

1.1.3.1. Binary (Also known as a bi-level image)

Logical array containing only 0s and 1s indicates black or white, respectively. A binary image is stored as a logical array. Figure 1.1 shows a binary image with a close-up view of some of the pixels' values.

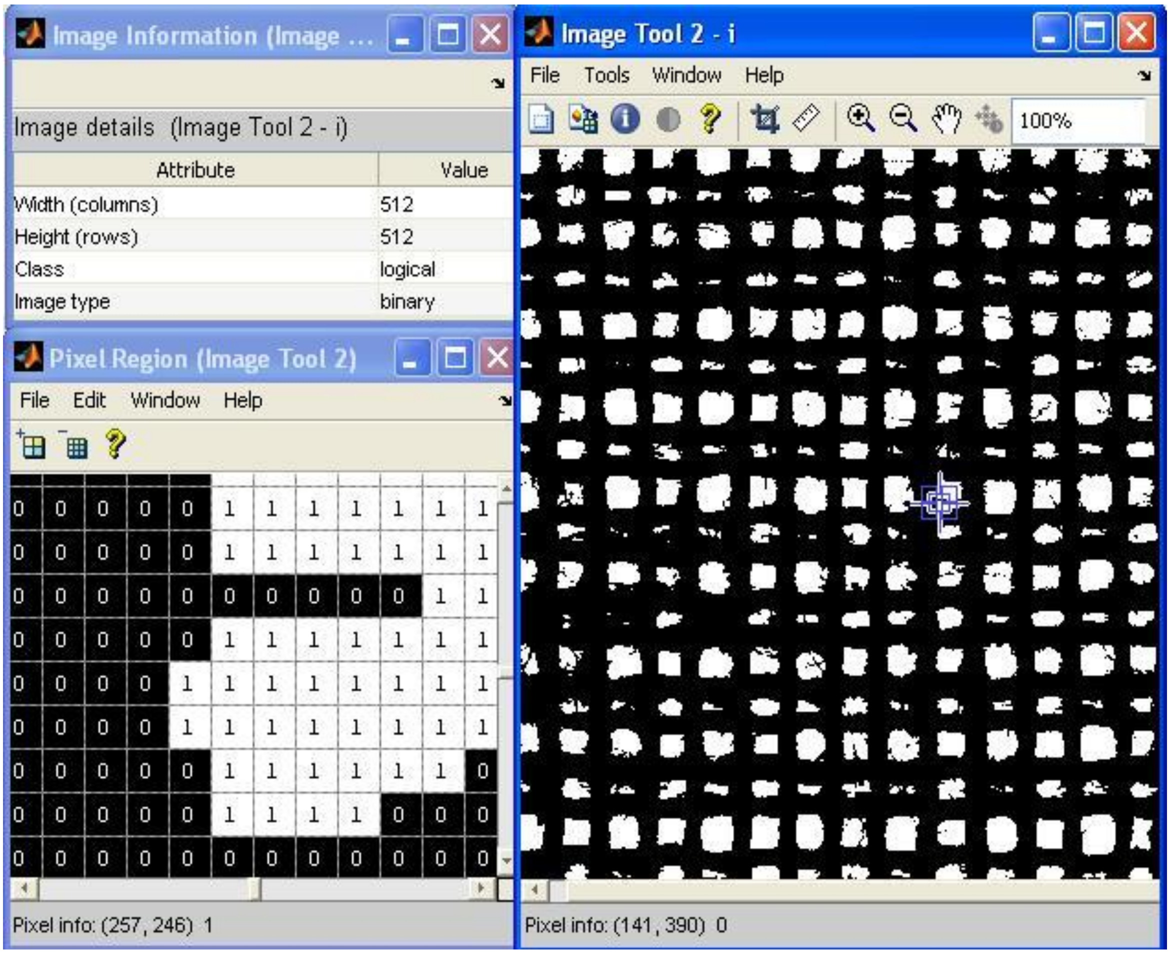

Figure 1.1: binary image.

1.1.3.2. Gray scale

Gray scale is also known as an intensity gray scale or gray level image. Each pixel indicates the intensity of light with in some range in its region. There is a color map to know the range of the pixel value. Its form is M-by-N array of class uint8, int16, uint16, single, or double. For single or double arrays storing, values range from [0, 1], For uint8 storing, values range from [0,255], For uint16 storing, values range from [0, 65535]. For int16 storing, values range from [-32768, 32767]. Figure 1.2 shows a gray scale image of class unit8.

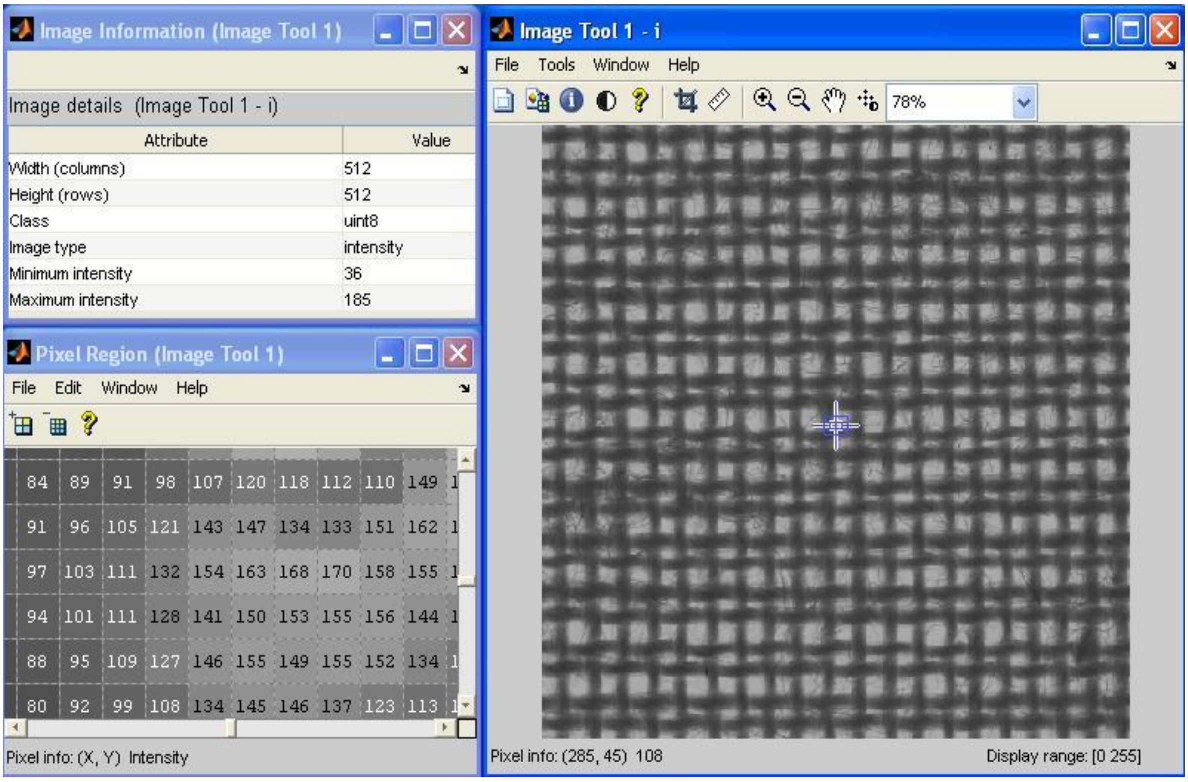

Figure 1.2: Gray scale image.

1.1.3.3. True color

Each pixel indicates the intensity of light with in some range in its region. There is no color map. Its form is M-by-N-by-3 array of class uint8, uint16, single, or double. For single or double arrays storing, values range from [0, 1]. For uint8 storing values range from [0,255]. For uint16 storing values range from [0, 65535]. Each pixel had 3 values for red, green, blue and there combination indicates its color. The three color components for each pixel are stored along the third dimension of the data array. For example, the red, green, and blue color components of the pixel (30,15) are stored in RGB(30,15,1), RGB(30,15,2), and RGB(30,15,3), respectively. Some graphics file formats store true color images as 24-bit images, where the red, green, and blue components are 8 bits each, this yields a potential of 16 million colors. Figure 1.3 shows a True color image of class unit8.

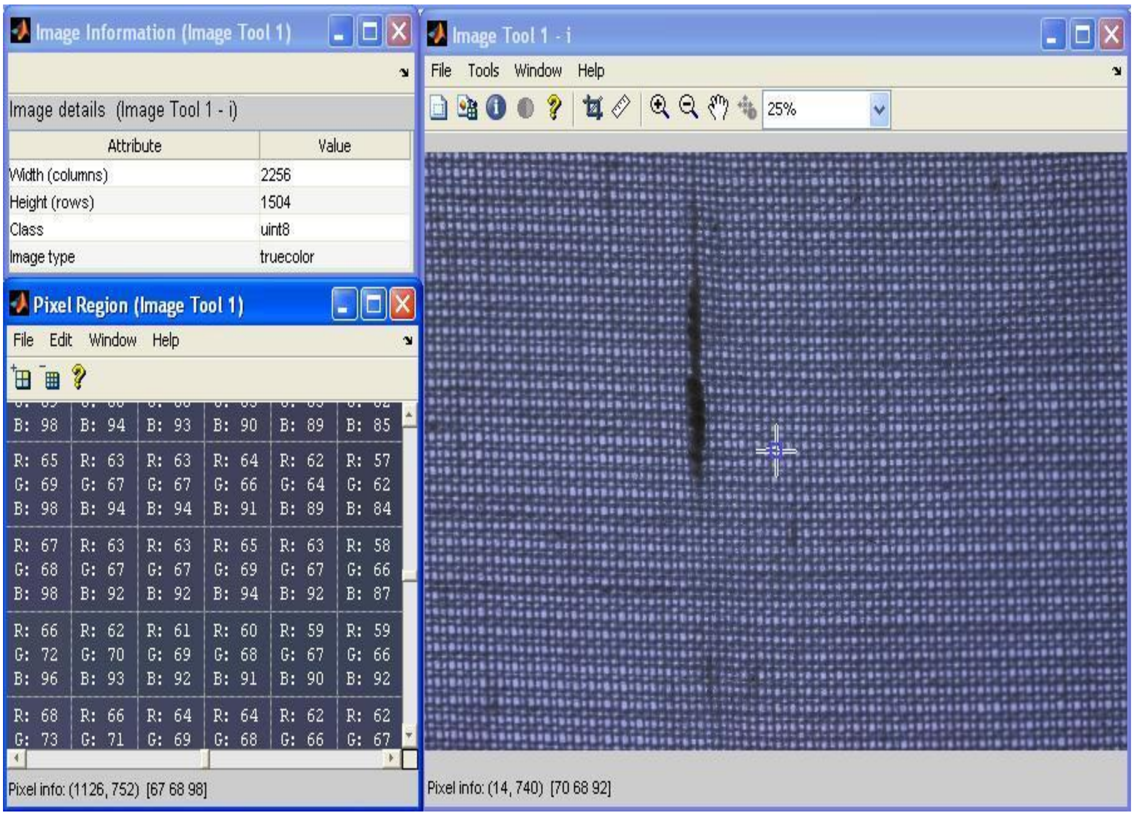

Figure 1.3: True color image.

1.1.3.4. Indexed Images

An indexed image consists of an array and a color map matrix. The pixel values in the array are direct indices into a color map.

1.2. Project Approach

Figure 1.4 shows a general diagrammatic sketch for an automated system using a computer for woven fabric defect detection, classification. The system also determines the sources of detected defects. Fabric images will be acquired by a digital camera.

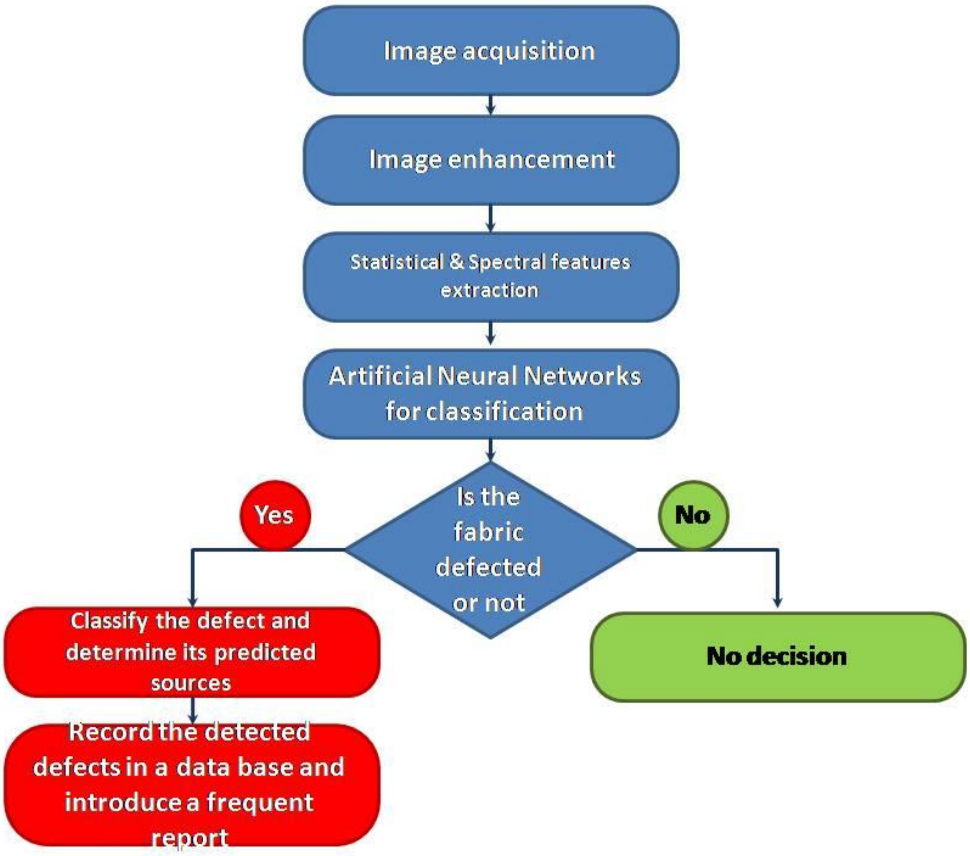

Figure 1.4: A diagrammatic sketch of the automatic system for woven fabric defects detection and classification.

The image acquisition process will utilize filters for image enhancement and standardization. Then, the image will be transmitted to a computer to extract some features. After that, these features enter an Artificial Neural Networks which is one of the most famous Artificial Intelligence Systems used as a classifier. The Artificial Neural Networks mimic the human mind and his ability to distinguish things by learning and correcting mistakes when happen.

This needs a number of free defect images and some others defective for the Artificial Neural Networks supervised training after building it then, some other images were chosen for determining the efficiency of the system for faults detection and classification. After classification the system determine the predicted sources for this fault and takes a decision for correcting it and for not being repeated. The system also record the detected defects in a data base to introduce a periodic report about the most frequent defects and its effect on the quality of the produced fabrics.

A design of an automatic inspection machine is introduced for building the system of image acquisition, image enhancement, image analysis, features extraction and defects classification. This machine can work for a number of weaving machines at the same time. The design of this machine is adaptable for its function and easy for moving in small places.

This project is an automatic inspection machine using the computer for automatic fabric defects detecting. This system increases the quality of the final product by detecting small defects and providing a periodic report to repair their sources. By Appling this system we will avoid human tiring and boring.

CHAPTER 2

REVIEW OF LITERATURE

Chapter 2

Review of literature

Several researches in textile field have utilized image processing techniques in many applications:

1) Fibers
2) Yarns
3) Fabrics

2.1 Fibers:

Tantaswadi et al. utilized an image analysis technique to inspect the quality of cotton fibers using color discrimination. The cotton image was analyzed for impurities using this iso-discrimination contour. This research referred to the important factors for color image processing which are lighting system (under controlled environment), video camera setting, and image processing algorithms such as edge detection and reduced 3D-LUT (3-dimensional lookup table) technique [7].

Ikiz et al. presented an application of image processing of fibers to measure fiber length. The results showed that image processing can measure fiber length more accurately and more precisely than hand measurement with high-resolution images. This technology was able to replace current fiber length measurement methods [8].

Xu and Huang utilized an image analysis for cotton fiber cross-section to measure fiber fineness and maturity. Their algorithms increased the automation and accuracy of separating touching fibers, identifying lumens and taking measurements pertaining to cotton fineness and maturity. All the measurements had more variations when fewer fibers were analyzed [9].

Also, Rodgers et al. measured two of the most important cotton fiber quality and processing parameters, fiber maturity and fineness. A new instrument used polarized light microscopy and image analysis in a water-based system to measure fiber maturity and fineness. The new method was rapid, precise and accurate using the Cotton scope. The major operational impact on the Cotton scope results was the environmental condition (location temperature and relative humidity) under which the measurement was performed [10].

Xu et al. presented a new method of measuring the number-length distribution of cotton fibers using a snippet-counting method and image analysis techniques. An imaging system was used to scan, trace, and count the snippets distributed on a glossy black paper. From the number-length data, the distribution, maximum length, mean length, and other fiber statistics was computed [11].

Wan et al. developed a method of creating fiber clusters using image analysis. Fiber clusters are often created by fiber cross-sectioning in microscopic images, in which fibers touch or overlap each other. The new algorithm based on the image processing set theory had success to separate clustered fibers in cross-section images. The experimental results demonstrated that the new algorithm could optimally separate clustered fibers of various cross-sectional shapes, including W-shaped and cross-shaped fibers [12].

Wang et al. proved that pseudo-foreign fibers in cotton could be detected by image analysis. A new foreign fiber detection platform was introduced by investigating several methods for image enhancement. By comparing the methods' enhance effects and algorithm speeds, results indicated that the Variational Retinex was suitable for on-line pseudo foreign fiber detection [13].

2.2 Yarns:

Chiu et al. applied image processing techniques to analyze cross sections of a PET/Rayon composite yarn and obtain single fiber positions in the image with mask processing. They reasonably analyzed fiber distributions of composite yam cross sections with three indexes: radial, lateral, and angular distribution. The experimental results proved the good performance of the ultra-microtome and the process of making the samples [14].

Chiu et al. used an image processing technique and neural networks to classify the quality grades of FTY (false twist yarn) packages. They extracted the defect features of FTY packages, such as size, discoloration, formation and cross-over. From the experimental results, they obtained 90% of classifying rate [15].

Gang et al. proposed a computerized method for automatic measurement and recognition of yarn wet snarls from an image of snarled yarn samples captured in a water bath. The development of an automatic measurement and recognition method of yarn snarl features was devoted by the applications of (Fast Fourier Transform) FFT and (Adaptive Orientated Orthogonal) AOP methods. The results showed that the proposed method was reasonably robust to these variations in the recognition of yarn snarl features [16].

Pan et al. constructed an automatic recognition system based on image analysis to identify the density, the color effect, the layout of color yarns and the woven pattern of yarn-dyed fabric. Experiments on actual yarn-dyed fabrics showed that the recognition system used was effectively detecting the structure parameters of yarn-dyed fabric. [17].

Ta`pias et al. derived the mean yarn diameter from partial cover factor (CF) estimates. The results were compared to the mean yarn diameter directly measured from images. They developed a fully automatic method, based on image processing techniques that yielded CF, partial CFs, yarn linear densities and yarn diameters of a woven fabric sample, with no intervention of a human operator, from a B/W digital image of the fabric [18].

Liu et al. used image processing to create a novel method for describing yarn evenness in fabric (YEF) instead of the traditional approach. The traditional approach usually described yarn unevenness characterization based on the CV (i.e. coefficient of variation) of mass between defined portions of yarn measured with the USTER evenness tester. Experimental results on virtual and physical woven fabric expressed that the method mentioned could get the fine information of the yarn from the fabric in detail [19].

2.3 Fabrics:

Huang et al. proposed a new image processing approach for identifying three weave patterns of woven fabrics; plain, twill, and satin weave sand automatically displaying harness drafts and chain drafts. Also fabric counts were measured by this method and got a good agreement with manual measurements based on the maximum and minimum gray-level sums of the horizontal and vertical pixel lines [20].

Kang et al. illustrated the stereo vision technique and its image processing for 3D measurements of surface contours to measure the smoothness appearance of fabric surfaces. The results showed that this method was more accurate for measuring fabric smoothness than the visual assessment. This system could use other surface evaluations such as wrinkles, seam puckers, or plain strain [21].

Sakaguchi et al. suggested image analysis for fabric quality evaluation as a substitute for human inspection of fabric surfaces. A fabric image was captured using a scanner. The peak width on the power spectrum of the surface intensity had a consistent relationship to fabric quality. This method based on the spectral peak width was useful for computerized evaluation of woven fabrics [22].

Kenkare and Plumlee introduced a modified method of measuring drape coefficient. The method was based on capturing image and processing the image to evaluate the fabric drape coefficient. The results showed that the modified method was similar to the conventional method for measuring fabric drape coefficient. This method reduced manual error of the conventional cut and weigh processes [23].

Özdemir and Bas introduced a new method that simulated fabric surface appearance from achieved yarn properties using image processing of yarn images. Computer simulation of woven fabric was transformed from a circle to an ellipse to imitate yarn flattening [24].

Naderpour et al. presented an application of image analysis to assess the fabric wrinkle and abrasion resistance. Sample images were captured by scanner, and then processed using a MATLAB code. The results revealed that data from image analysis was more precise and quicker than traditional experimental procedure, in addition to the significant reduction of human based errors [25].

Hadjianfar et al. measured fabric luster via image analysis. An index was obtained for the luster of fabrics by analyzing the luminance of fabrics which obtained by analyzing the photographs captured for fabric samples under the same conditions. The image processing based method was approved by both goniophotometric method and human vision [26].

2.4 Fabric Defects:

Mallik and Datta presented a theoretical based technique for real time fabric defect detection using a joint transform correlator that is an extension of Fourier transforms analysis. The joint power spectrum showed better classification results compared to the Fourier and experimental results. The joint transform correlation technique was implemented in an optical domain. The technique introduced good results for identifying and classifying some defects such as the existence of thick yarns, knots, and missing yarns [27].

Hu and Tsai used best wavelet packet transform and an artificial neural network (ANN) to inspect four kinds of fabric defects. Their approach was a reliable and effective for classifying fabric defects. The results showed that the total classification rate for a wavelet function with a maximum vanishing moment of four and three resolution levels can reach 100% [28].

Goswami and Datta used morphological operations such as erosion and opening to identify defects. A collimated laser beam was used for illumination. A spatial filter was placed at the Fourier plane to remove the periodic grating structure of the fabric from the image. This technique needed the execution of two Fourier transform operations followed by necessary morphological processing [29].

Huang and Honygu classified seven kinds of dyeing defects using image processing and fuzzy neural network approaches. Ten samples for each defect were obtained for training and testing. The results demonstrated that the fuzzy neural network approach could precisely classify these samples by the features selected [30].

Chihuuna and Hen presented a neural-fuzzy system to classify eight kinds of fabric defects. The neural-fuzzy system and neural network were implemented as classifiers and compared to each other. The results demonstrated that the neural-fuzzy system was superior to the neural network in classification ability [31].

Akagucghui et al. Applied image analysis to fabric quality evaluation as a substitute for human inspection of fabric surfaces. The coefficient of variation and power spectra of yam interval were calculated as features for fabric images captured by a scanner. The power spectral peak width of the intensity data was computed as another approach to the irregularity of fabric surfaces. This method based on the spectral peak width was useful for computerized evaluation of woven fabrics [32].

Wen et al. used wavelet transform and co-occurrence matrix to extract features of texture images. They used those features to locate defects on textile fabrics. The system was able to detect whether the fabric defective or not at 92% rate of success. On the other hand, it was able to locate the defect position at 84% rate of success [33].

Tilocca et al. presented a new direct approach for automatic fabric inspection based on an optical acquisition system and an artificial neural network (ANN). The ANN was trained to classify three different categories: normal fabric, defect with a marked 3D component, and defect with no 3D component. The response of this system was very fast, accurate and thus suitable for on-line monitoring of fabric defects at a high inspection rate without any transformation of data [34].

Kuo and Su applied the co-occurrence matrix and gray relational analysis of the gray theory. They extracted features of a fabric defect image and classify defects including broken warps, broken wefts, holes, and oil stains. They also used gray relational analysis to investigate correlations of the analyzed factors among the selected features in a randomized factor sequence through image processing. The corresponding recognition accuracy of the systems was 94% [35].

Shady et al. used image analysis and neural networks for six different knitted fabric defects detection and classification. They used statistical approaches and Fourier Transforms for feature extraction. Neural networks were used to detect and classify the defects. The results of using the Fourier Transform features extraction approach were slightly more successful than the statistical approach in detecting the free defect and classifying most of the other defects [36].

Liu et al. used and compared two different approaches for the extraction of images of slub yarns that was very important part in the development of a denim fabric recognition system. They used Gabor filters in both the time domain and the frequency domain respectively as a two different methods. The first method used the filter according to the designed cost function. The second method used the parameters of the Gabor filter. The results showed that both methods succeeded for slub recognition with better results of the second approach [37].

Yuen et al. designed an inspection method for evaluating fabric stitches or seams of knitted fabric. Nine characteristic variables were obtained from the segmented images and input into a Back Propagation (BP) neural network as a classifier for object recognition. The results demonstrated that the inspection method developed was effective with 100% recognition rate [38].

Bu et al. designed a new simple approach for fabric texture analysis based on the modern spectral analysis of a time series rather than the classical spectral analysis of an image. They made a one-dimensional power spectral density (PSD) analysis of the fabric image via a Burg-algorithm-based Auto-Regressive (AR) spectral estimation model. The detection results between the AR model and the FFT method were compared. The comparison showed that the new method gave a low false alarm rate and a low missing rate [39].

Lin used case-based reasoning (CBR) to detect fabric defects. A co-occurrence-based method was used for feature extraction. Six feature parameters were obtained. The results showed that fabric defects that inspected by the CBR demonstrated excellent performance with a 90% accuracy rate [40].

Malek represented an effective and accurate approach based on image processing software for automatic defect detection. He proposed a vision-based fabric inspection prototype that could be accomplished on-loom to inspect the fabric under construction with 100% coverage. The results of this study showed the success of using fast Fourier transform and cross-correlation for online automated fabric inspection [6].

CHAPTER 3

PROBLEM STATEMENT

Chapter 3

Problem Statement

In the weaving mills human visual inspection process only detects 60 to 70% out of the total fabric defects [1] while the residual defects pass without detection. This causes several problems in the following processes of manufacturing. Several researchers try to solve this problem using image processing techniques. All the previous trials classified little number of defects while this is not enough for detection in weaving mills. This project introduces an automated system to detect and classify a large number of woven fabric defects replacing the conventional inspection process.

Our proposed system utilizes a digital camera to acquire and transmit fabric images to a computer which enhance and extracts the features for each image. Then, the features are processed using Artificial Intelligence technique to detect and classify the fabric defects. Also, this automated system will be able to predict the sources of the defect to be fixed. These defects will be recorded in a data base to provide a periodic report including the frequent defects to fix their sources and hence increase the quality of the manufactured fabrics. Applying such automatic system in weaving mills will increase the product quality.

CHAPTER 4

EXPERIMENTAL WORK

Chapter 4

Experimental Work

The woven fabric usually consists of two interlacing groups of yarns each of which is perpendicular to the other. One group is in the weaving machine direction which includes the warp yarns. Yarns in the other group are called weft or fill yarns. The interlaced yarns construct a repeat of weave structure. Any change in this repeat usually represents a fabric defect. The majority of fabric defects are made during the weaving process where some others are from the previous yarns manufacturing processes.

The defects are generally categorized into three main categories; defects in warp yarns, defects in weft yarns and defects in area. Defects in warp yarns are double end, coarse end, broken end, tight end, warp streak, end out, mixed end, tight twist end, soiled end, missed end and float warp. Defects in weft yarns are mispick, broken pick, coarse pick, hang pick, stop mark, double pick, mixed filling, heavy peat, light peat and missing Picks. Area defects are hole, color staining, fuzz ball, finger mark, gout, float, smash, knot and stain.

4.1. Materials:

Weaving is the technology by which yarns are transformed into fabrics. The idea of weaving based on interlacing two groups of yarns each of which is perpendicular to the other. One group is in the weaving machine direction which includes the warp yarns. Yarns in the other group are called weft or fill yarns. The samples used in this project are manufactured in Samanoud Co. for woven and pile fabrics. The samples are manufactured on Sulzer-Ruti weaving machine. The machine speed is 220 R.P.M. and number of dents per cm is 9.4. Cotton/Polyester (35/65) blended yarns are used to manufacture the fabric. The manufactured fabric is plain weave 1/1, its width is 100 cm and number of warp yarns per dent is 2. Yarn's count is 20/1 Ne for warp and 14/1 Ne for weft. The densities of warp and weft yarns in cm are 20 and 18 respectively.

The chosen defects were intentionally introduced on the machine based on the knowledge of defect sources. The defects are generally categorized into three main categories; defects in warp yarns, defects in weft yarns and defects in area. Defects in warp yarns are double end and a float warp. Defects in weft yarns are double pick, heavy peat, light peat and missing Picks. Area defects are hole, knot and stain. Descriptions and suggested causes for each fabric defects are as follows:

4.2. Fabric defects

4.2.1 Defects in warp direction

4.2.1.1 Double end

Description:

A departure from the continuity of the weave pattern caused by the one or more ends weaving in the wrong order.

Cause:

Wrong drawing, taking more ends in healed eye or wrong denting, taking one or more ends in a wrong dent.

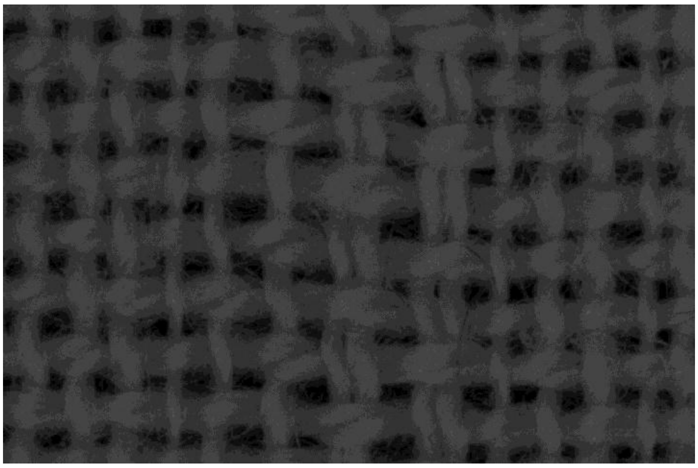

Figure 4.1: Double end.

4.2.1.2 A float warp

Description:

A defect in which warp yarn extends unbound over the ends with which it should be interlaced.

Cause:

Defected heald.

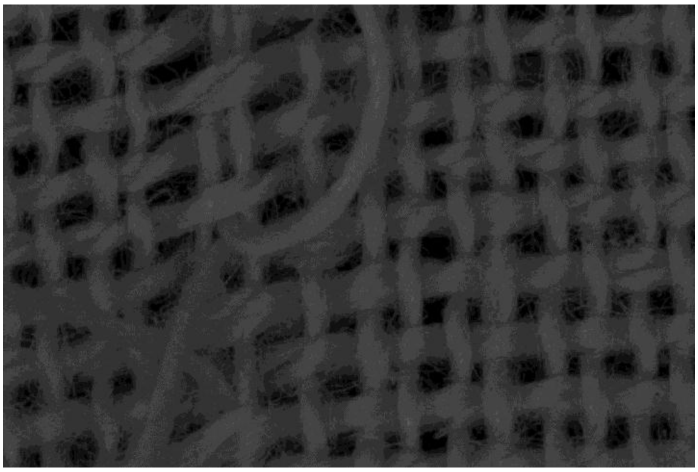

Figure 4.2: Float Warp.

4.2.2 Defects in weft direction

4.2.2.1 Double Pick

Description:

Two picks wrongly placed in the same shed.

Cause:

Incorrect picking.

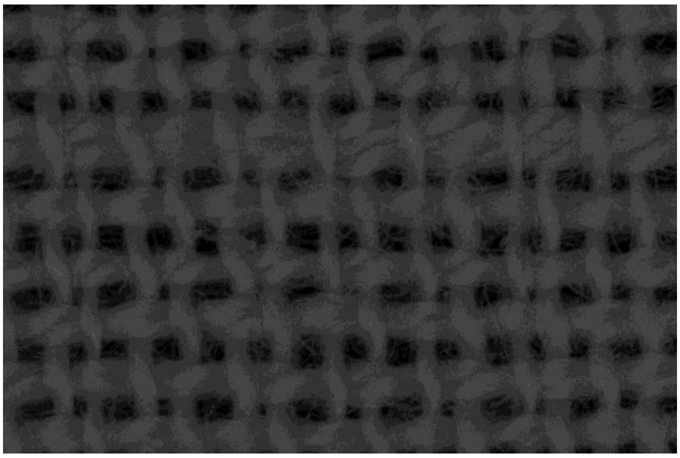

Figure 4.3: Double Pick.

4.2.2.2 Heavy beat

Description:

An increase in the density of the weft yarns.

Cause:

Faulty let-off and take-up motion.

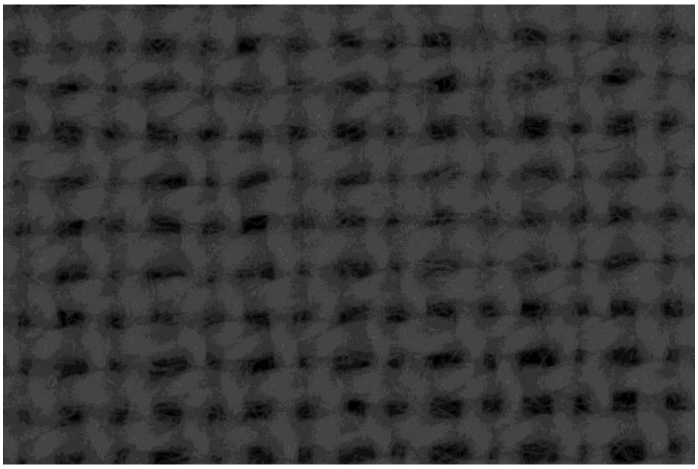

Figure 4.4: Heavy Beat.

4.2.2.3 Light beat

Description:

A decrease in the density of the weft yarns.

Cause:

Faulty let-off and take-up motion.

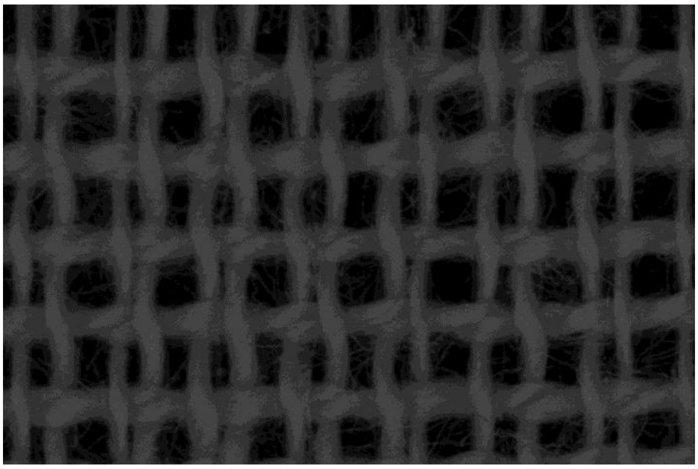

Figure 4.5: Light Beat.

4.2.2.4 Missing Picks

Description:

A narrow streak running parallel with weft threads caused due to absence of weft.

Cause:

Faulty let-off and take-up motion or faulty weft-stop motion.

Figure 4.6: Missing Picks.

4.2.3 Spatial Defects (Area)

4.2.3.1 Hole

Description:

An imperfection where one or more yarns are sufficiently damaged to create an aperture.

Cause:

A broken projectile guide falling over the fabric roll.

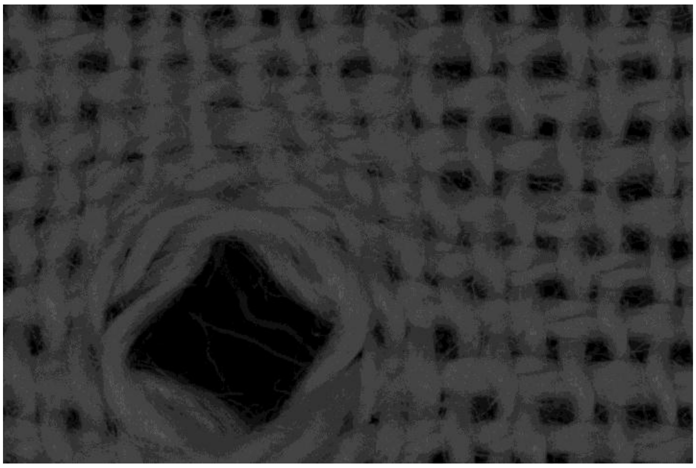

Figure 4.7: Hole.

4.2.3.2 Knot

Description:

A fastening made by tying together the ends of yarn**.**

Cause:

Thread breaks during process of winding, warping, sizing or weaving**.**

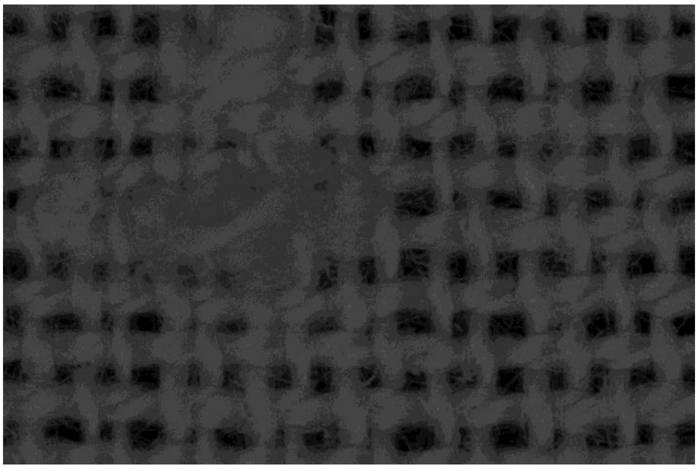

Figure 4.8: knot.

4.2.3.1 Stain

Description:

Spot defects of oil, rust, grease or other stains found in the fabric**.**

Cause:

Improper oiling/greasing of looms or Oil stained take up roller.

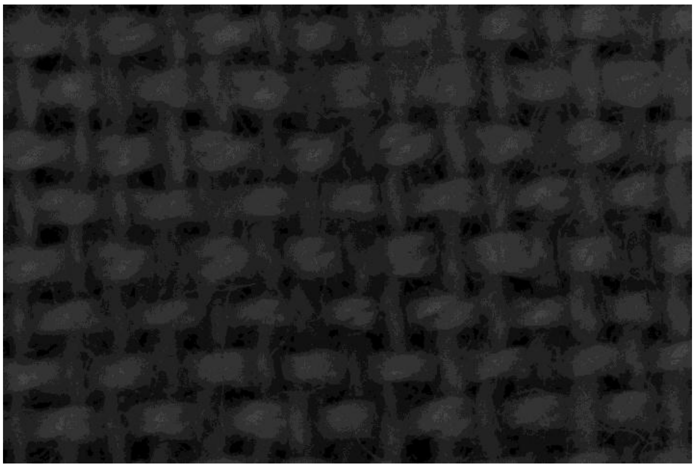

Figure 4.9: Stain.

4.2.3.2 Big Knot

Description:

A foreign matter accidently woven into the fabric**.**

Cause:

Improper loom cleaning or unclean environment**.**

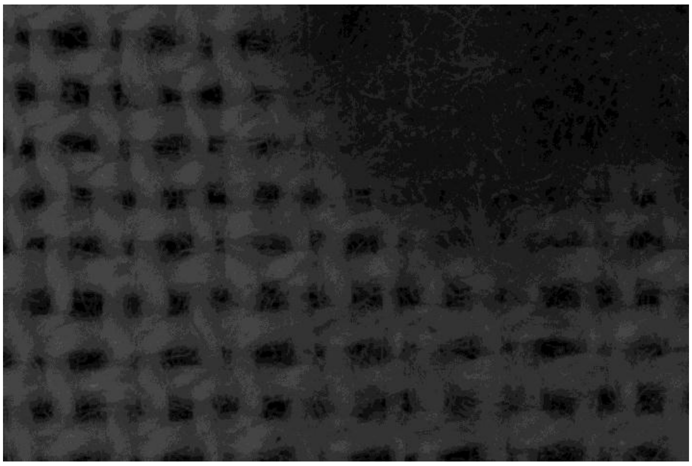

Figure 4.10: Big Knot.

4.3 Automatic vision system

4.3.1 Camera canon EOS 450D

4.3.1.1 Type

Recording media: SD memory card.

Image sensor size: 22.2 mm x 14.8 mm.

Compatible lenses: Canon EF lenses (including EF-S lenses) (35mm-equivalent focal length is approx.1.6 times the lens focal length).

4.3.1.2 Image Sensor

Type: High-sensitivity, high-resolution, large single-plate CMOS sensor.

Pixels: Effective pixels: Approx. 12.20 megapixels.

4.3.1.3 Recording System

Image type: JPEG.

(1) Large / Fine: Approx. 4.3 MB (4272 x 2848 pixels).

(2) Large / Normal: Approx. 2.2 MB (4272 x 2848 pixels).

(3) Medium / Fine: Approx. 2.5 MB (3088 x 2056 pixels)

(4) Medium / Normal: Approx. 1.3 MB (3088 x 2056 pixels)

(5) Small / Fine: Approx. 1.6 MB (2256 x 1504 pixels)

(6) Small / Normal: Approx. 0.8 MB (2256 x 1504 pixels)

(7) RAW: Approx. 15.3 MB (4272 x 2848 pixels)

File numbering: Consecutive numbering, auto reset, manual reset

4.3.1.4 Image Processing

Color space: Adobe RGB.

Picture Styles: Standard, Portrait, Landscape, Neutral, Faithful, Monochrome.

White balance: Auto, daylight, shade, cloudy, tungsten, white fluorescent light, flash, custom.

4.3.1.5 Exposure Control

Metering modes: 35-zone TTL full-aperture metering

• Evaluative metering (linkable to any AF point)

• Partial metering (approx. 9% of viewfinder at center)

• Spot metering (approx. 4% of viewfinder at center)

• Center-weighted average metering

Exposure control: Program AE (Full Auto, Portrait, Landscape, Close-up, Sports, Night Portrait, Flash Off, Program), shutter-priority AE, aperture-priority AE, depth-of-field AE, manual exposure, E-TTL II auto flash

ISO speed (Recommended Exposure Index):

Basic Zone modes: ISO 100 - 800 set automatically

Creative Zone modes: ISO 100 - 1600

4.3.1.6 Shutter

Type: Electronically-controlled, focal-plane shutter.

Shutter speeds: 1/4000 sec. to 1/60 sec., X-sync at 1/200 sec.1/4000 sec. to 30 sec., bulb (Total shutter speed range. Available range varies by shooting mode.)

4.3.1.7 Live View Functions

Shooting modes

(1) Live View shooting

(2) Remote Live View shooting (with a personal computer installed with EOS Utility)

4.3.1.8 Interface

USB terminal: For personal computer communication and direct printing (Hi-Speed USB)

Video OUT terminal: NTSC/PAL selectable

4.3.1.9 Dimensions and Weight

Dimensions (W x H x D): 128.8 x 97.5 x 61.9 mm / 5.1 x 3.8 x 2.4 in.

Weight: Approx. 475 g / 16.8 oz. (body only)

4.3.1.10 Battery Pack LP-E5

Type: Rechargeable lithium ion battery

Rated voltage: 7.4 V DC

Battery capacity: 1080 m Ah

Dimensions (W x H x D): 36 x 14.7 x 53.1 mm / 1.4 x 0.6 x 2.1 in.

Weight: Approx. 50 g / 1.8 oz. (excluding protective cover)

4.3.1.11 Battery Charger LC-E5

Compatible battery: Battery Pack LP-E5

Recharging time: Approx. 2 hours

Rated input: 100 - 240 V AC (50/60 Hz)

Rated output: 8.4 V DC/700 mA

Dimensions (W x H x D): 67 x 26 x 87.5 mm / 2.6 x 1.0 x 3.4 in.

Weight: Approx. 80 g / 2.8 oz.[45]

4.3.2 Lens EF100mm f/2.8L MACRO IS USM

Focal length /Aperture: 100mm f/2.8.

Min. Focusing Distance: 0.3 m/1.0 ft.

Field of view: 24 x 36 mm /0.9 x1.4 in. (at 0.3m)

Max. Diameter and Length: 77.7 x 123 mm /3.1 x 4.8 in.

Weight: 625 g /22.0 oz [46].

4.3.3 Personal computer

Computer Lenovo G580

Processor Intel® core ™ i3 -3110M CPU @ 2.40GHz

Installed memory (RAM): 4.00 GB

Video graphics: 1 GB, NVidia GeForce GT 610M

Hard drive: 500 GB, 5400 rpm

4.3.4 Model for Fabric Faults Inspection machine

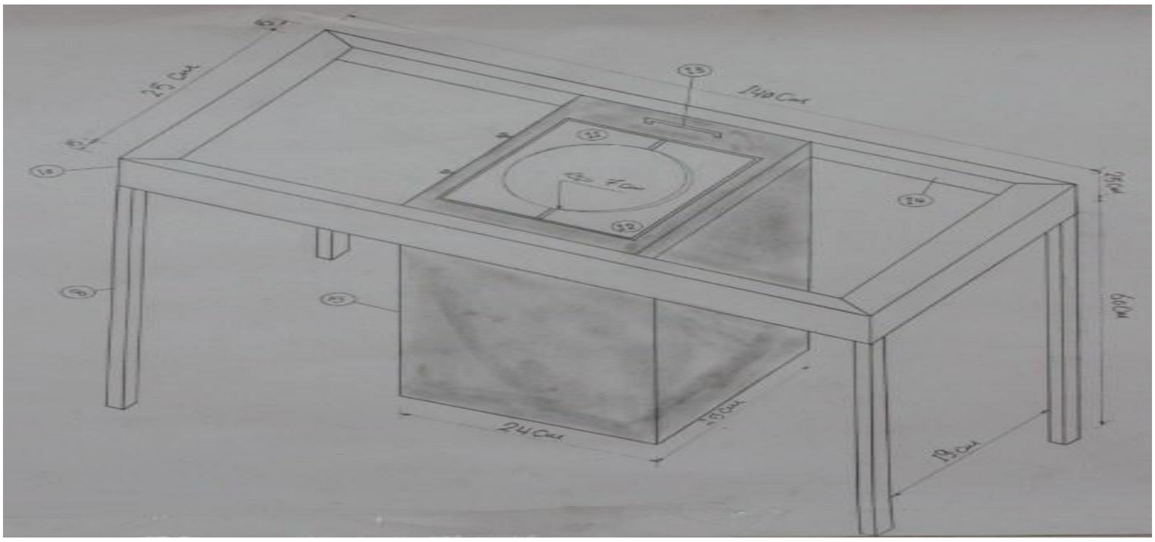

Figure 4.11: Upper model structures.

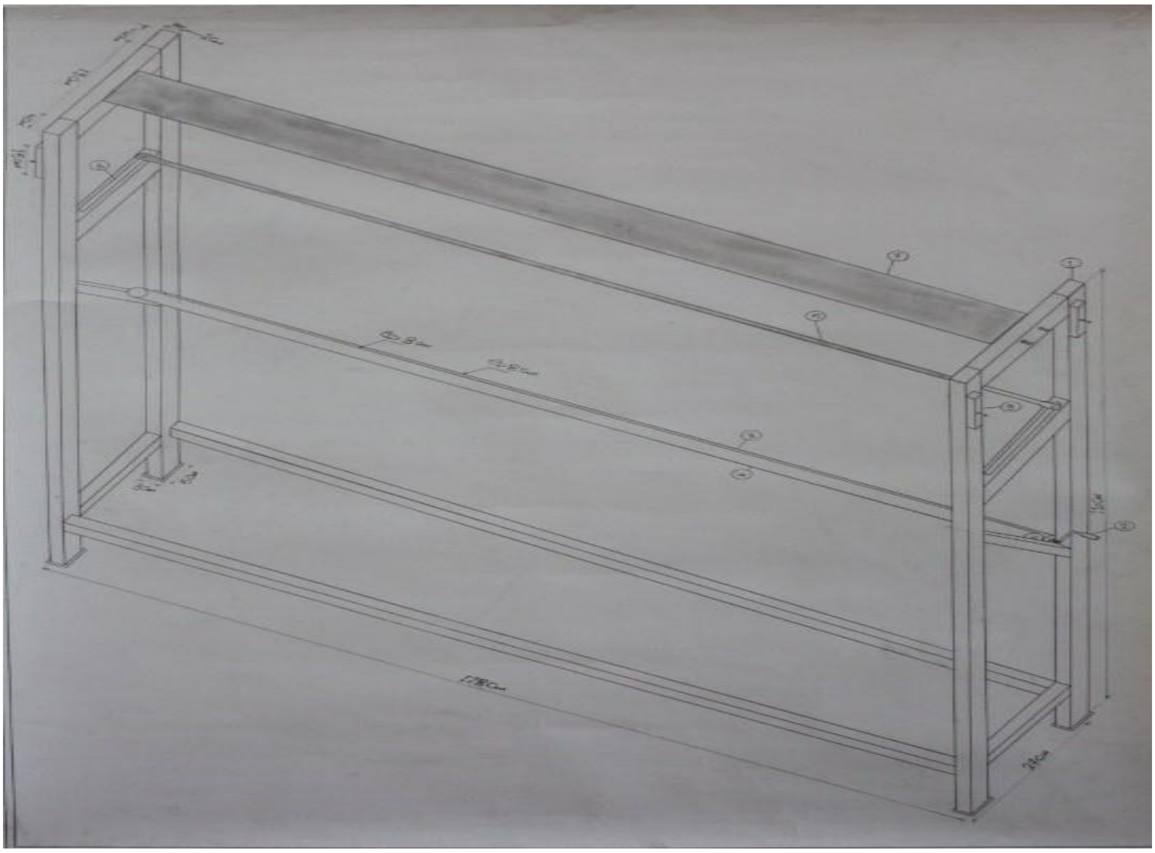

Figure 4.12: Lower model structures.

Figure 4.12: Real image for machine.

4.3.4.1 Components of model

1- Lower model structures. 2- Hand of operating.

3- Fabric let-of roller. 4- Fabric take-up roller.

5- Fabric guide. 6- Fabric guide stream.

7- Examination guide. 8- Four arms.

9- Arm's guides. 10- Upper model structures.

11- The right half of the camera holder.

12- The left half of the camera holder. 13- Camera holder moving hand.

14- Camera holder guide. 15- Light box.

Figure 4.13: Real image for lower model structures.

Figure 4.14: Real image for Hand of operating.

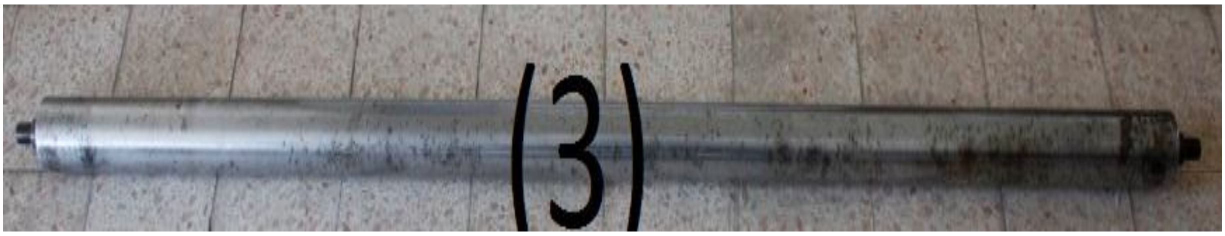

Figure 4.15: Real image for Fabric let-of roller.

Figure 4.16: Real image for Fabric take-up roller.

Figure 4.17: Real image for fabric guide and stream guide.

Figure 4.18: Real image for Examination guide.

Figure 4.19: Real image for Arm's guides.

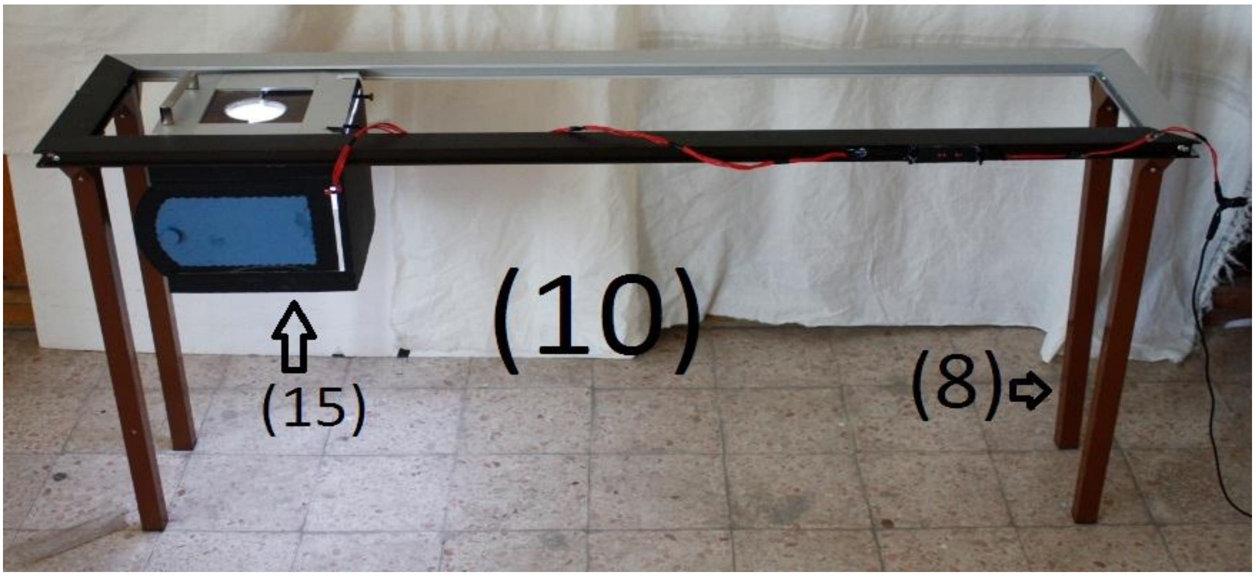

Figure 4.20: Real image for Upper model structures and four arm's.

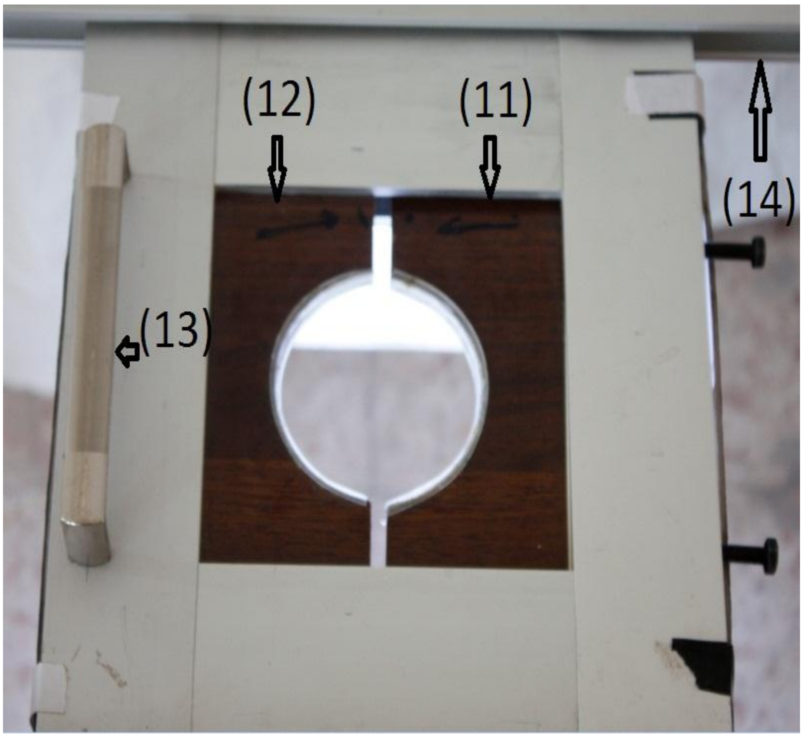

Figure 4.21: Real image for left , right , hand and guide move holder camera.

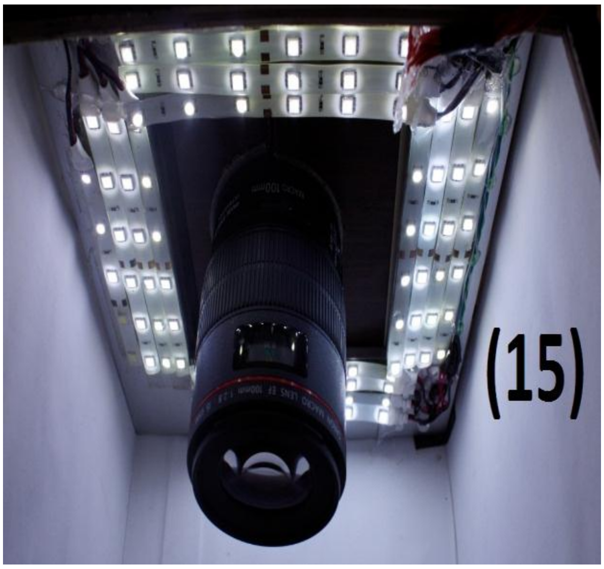

Figure 4.22: Real image for light box.

4.3.4.2 Method of operation

The fabric Is loosen to be examined from Roller (4) to pass the examination guide (7) where the camera acquires images for fabric and then passes on fabric guide (5) to Fold Roll (3) that is operated manually (2). Both let off and take up roller are rotating by friction depending on their weight and the inclined angle of the roller setting. The amount of fabric tension is controlled by moving guide (5) within the stream guide (6). The camera is fixed between the two segments (1), (2) which are moving inside the camera holder. The carrier is moved manually (13) to the left and to the right. Light guide (15) is used to focus the light on the fabric sample and the camera is not affected by the outside light. Lights used consist of 16 led tapes every tape consists of six leds. The power of each two tapes two watts, 12 volts and six amp. Distance between camera and fabric is adjusted by moving the four arms (8) within the stream of the arms (9).

4.4 Image acquisition

Figure 4.23: The setting of image acquisition.

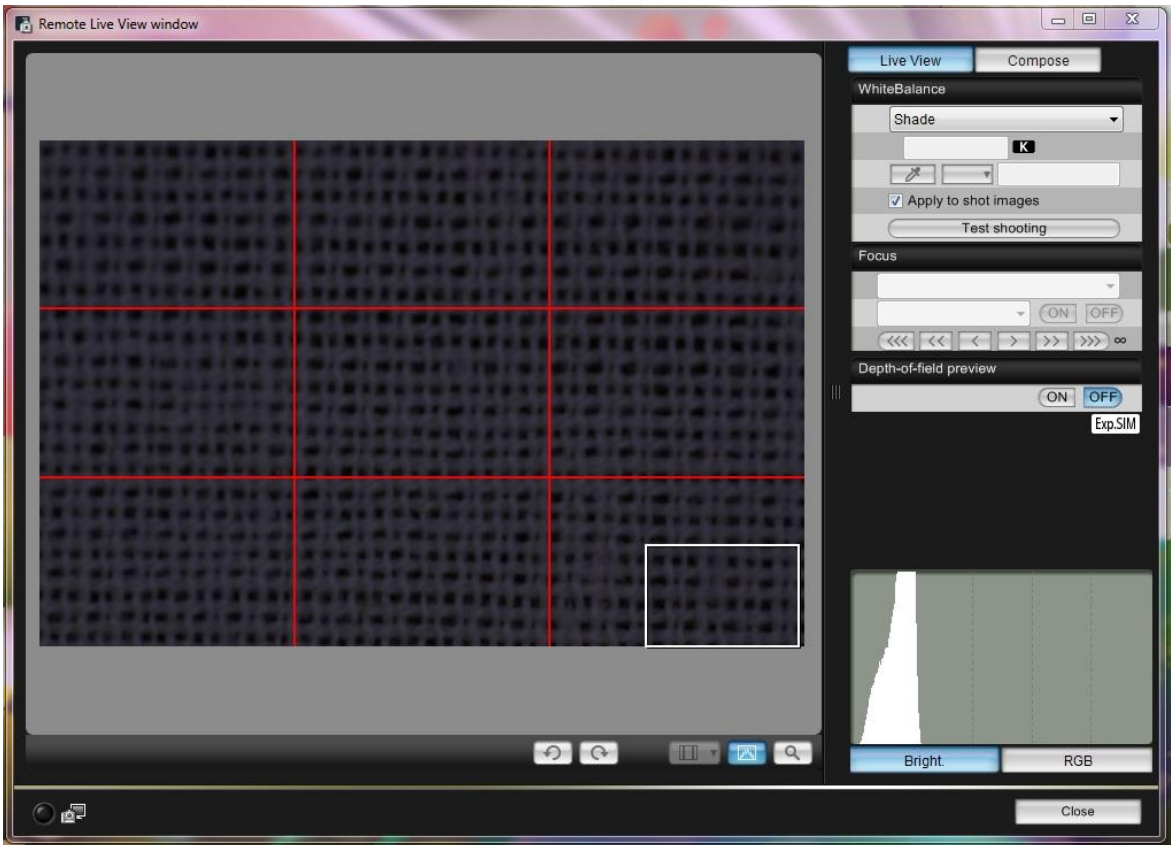

Figure 4.24: The interface of live view mode.

Images have been acquired using the automatic vision system. The distance between the lens of the camera and the fabric sample is adjusted to get the most vivid image which has good details of the yarns and interlacing areas. Also, the defective area should be distinguished easily. The distance between camera's lens and fabric is taken as 130 mm to get the best images. The dimensions of acquired images are (3088 x 2056 pixels) this represents (30 x 20 mm) of the fabric as showed in figure (4.25). This means every (1 mm^2) is represented by (100 x 100) pixels.

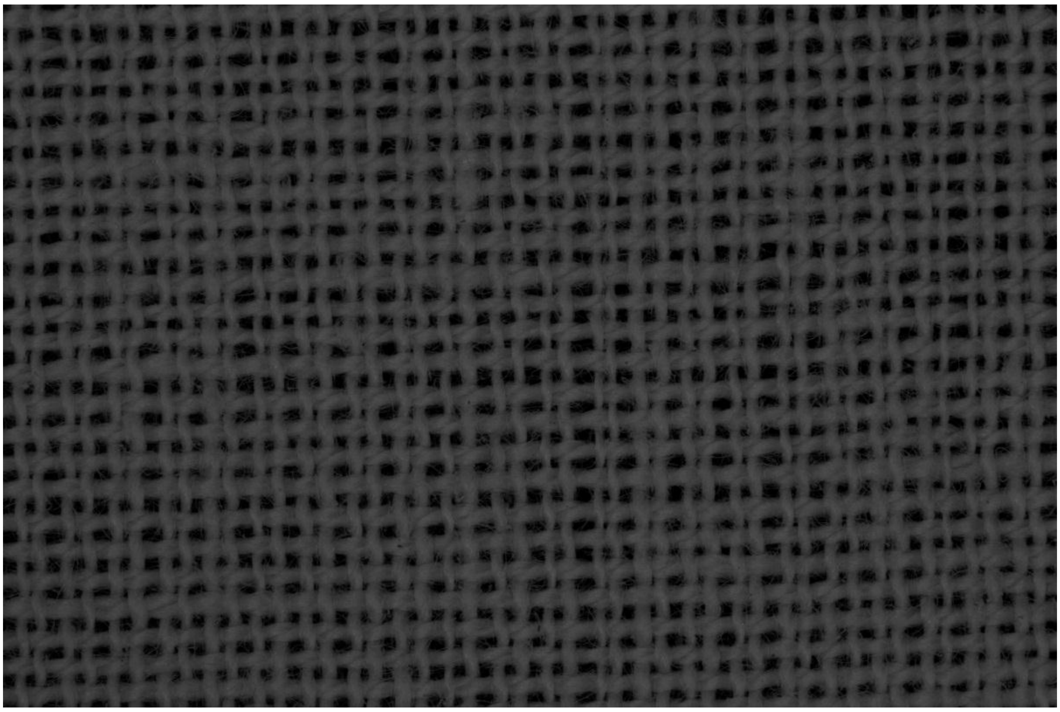

Figure 4.25: An image of fabric sample.

The dimensions of the acquired images were big for defects to be detected and classified correctly. Figure (4.26) each image has been divided into nine images. The divided images were suitable for clearing the defects.

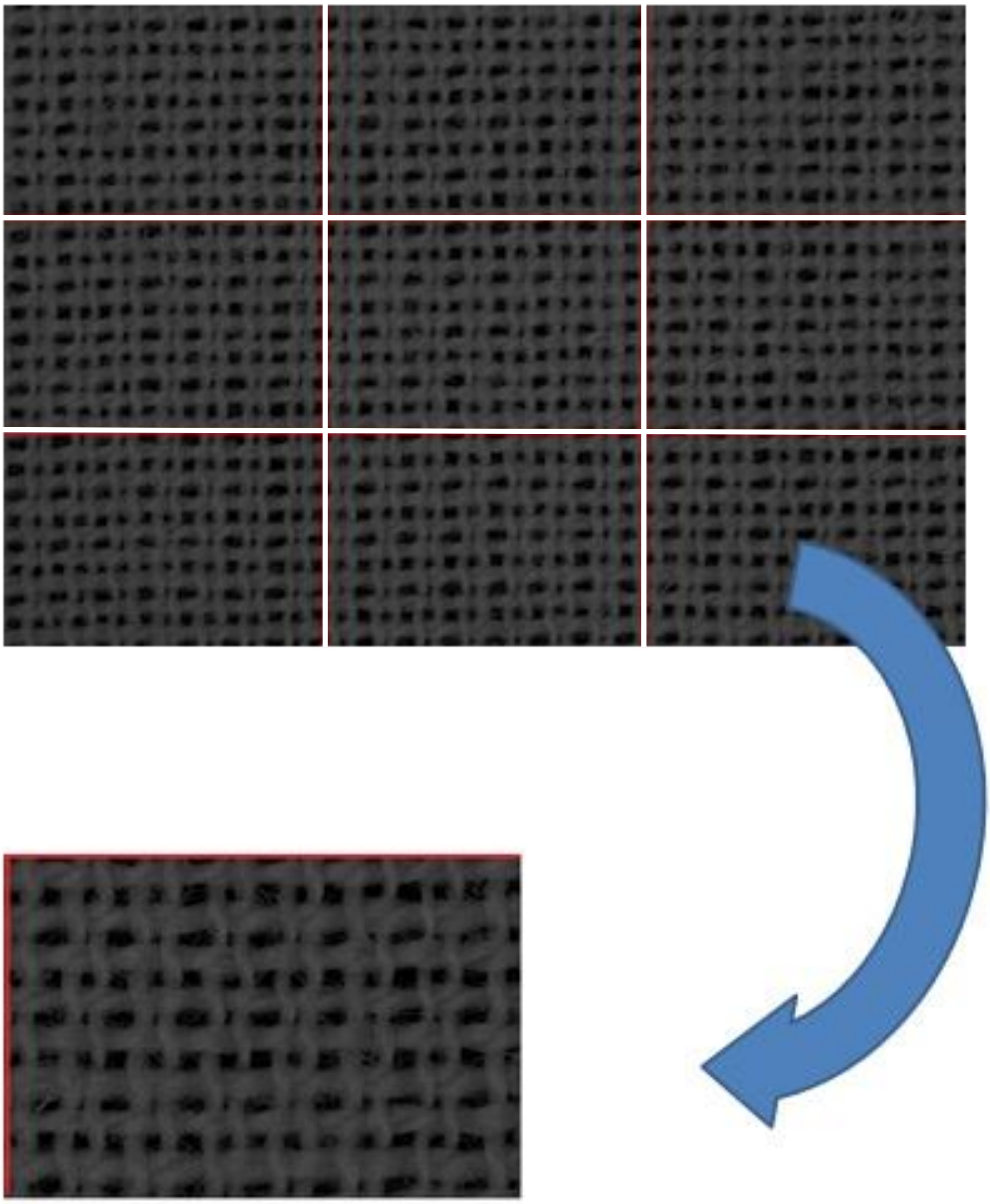

Figure 4.26: An image divided into nine small images.

CHAPTER 5

FEATURES' EXTRACTION

Chapter 5

Features' Extraction

Before applying any analysis on the image it is important to enhance the quality of the image to get better results.

5.1. Image Enhancement

Image enhancement is defined as the process of improving the quality of an image to make an image lighter or darker, or to increase or decrease contrast. Advanced image enhancement may be applied with many filters in various ways. The enhancement of woven fabric images should clear the yarns in the images to be suitable for features' extraction process.

Several approaches of image enhancement can be applied to remove hairness from the woven fabric images and to clear the yarns and defects as well. The following figures show an image and the effect of several approaches of enhancement on it.

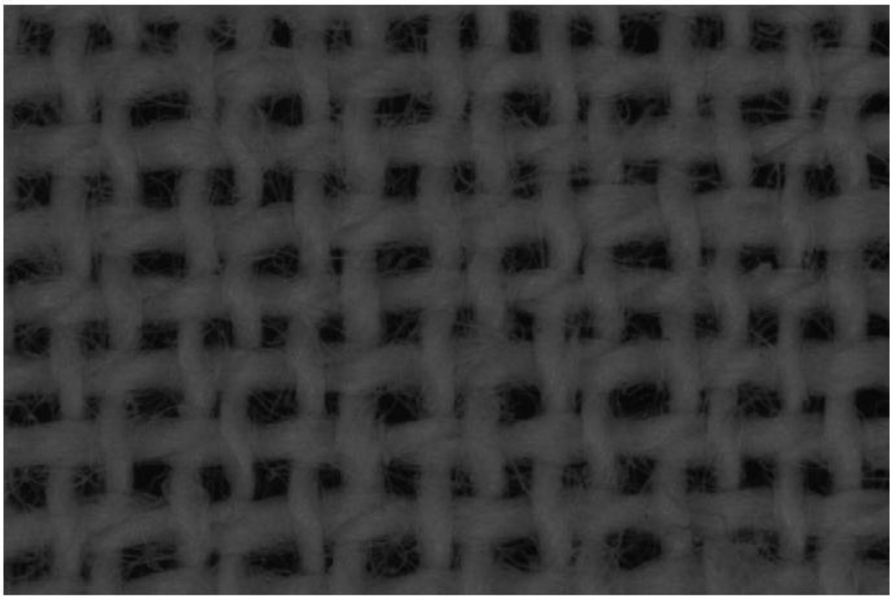

Figure 5.1: RGB image.

Figure (5.1) shown RGB image and For increasing the analysis speed it has been transformed to gray image with one layer matrix as shown in figure (5.2).

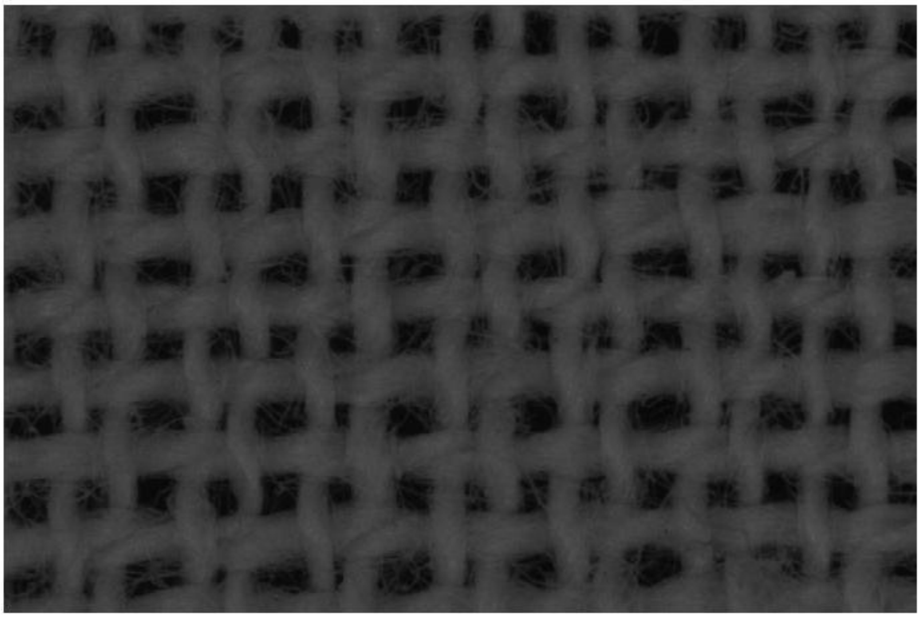

Figure 5.2: gray image.

5.1.1. Adjustment of gray levels

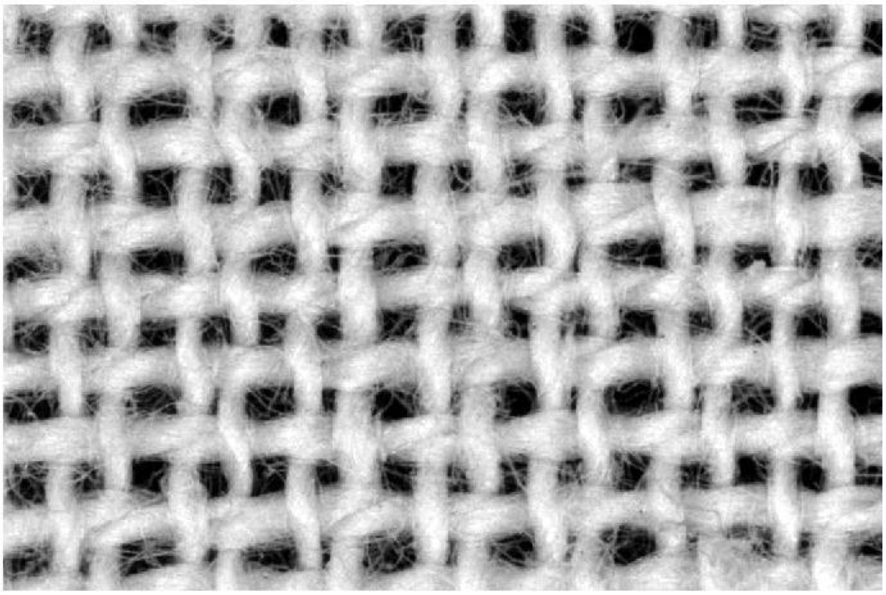

Figure 5.3: image in figure (5.2) after adjustment gray level.

5.1.2. Noise removing

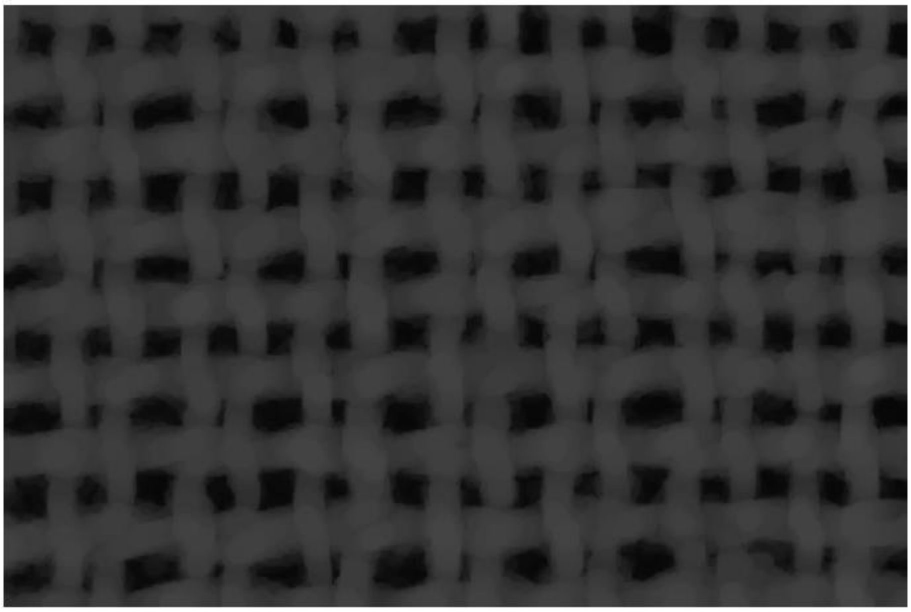

Figure 5.4: remove small noise in image figure (5.2).

Figure 5.5: noise image in figure (5.2).

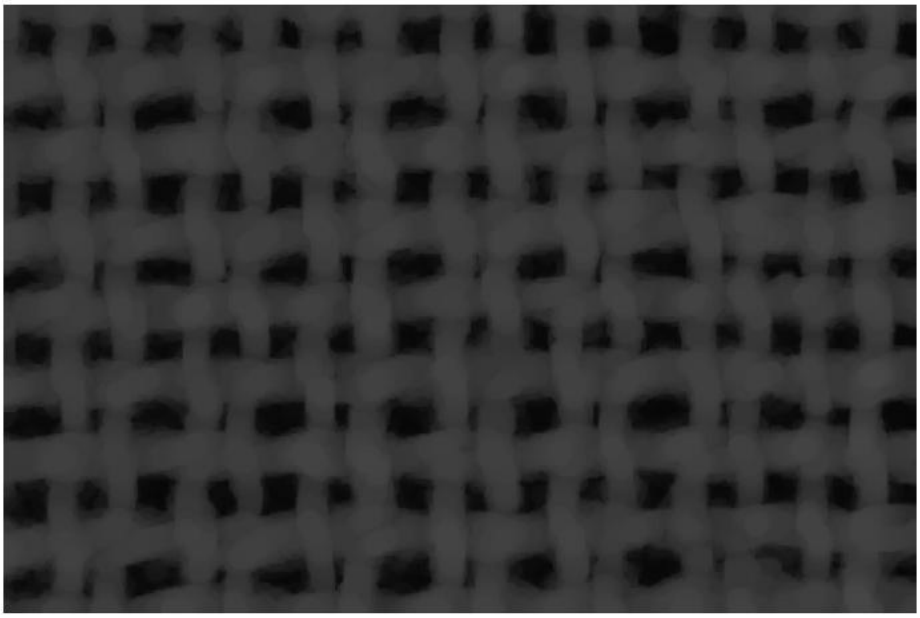

Figure 5.6: image in figure (5.2) - image in figure (5.5).

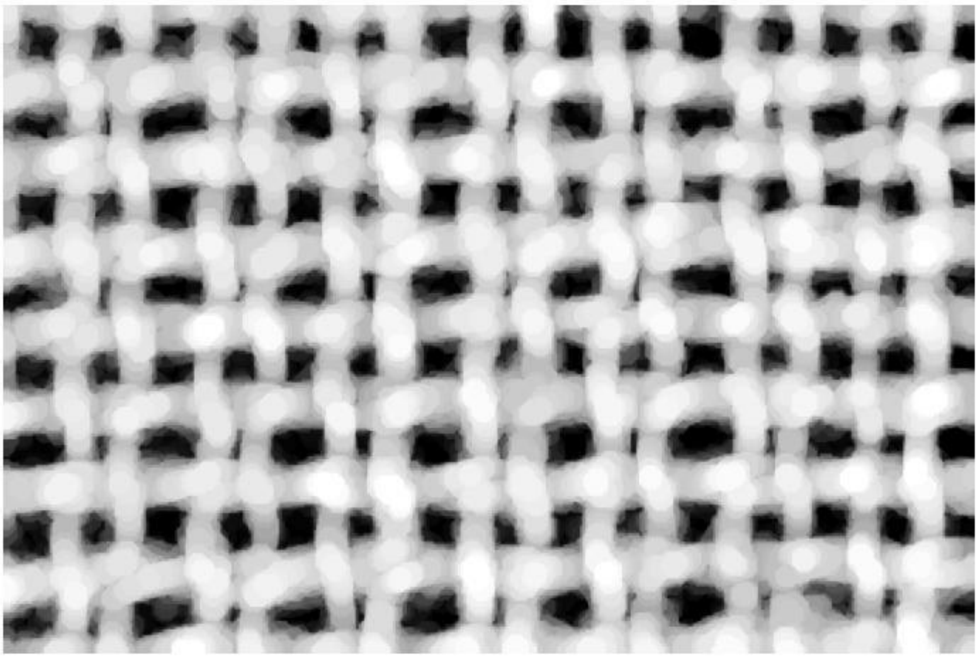

Figure 5.7: image in figure (5.2) after noise removal and gray level adjustment.

5.2. Features' extraction

The digital form of an image is a 2-D Matrix where each element of the matrix contains a value represents the intensity of light of this pixel. Each image has a huge number of pixels values. It is needed to have a one value which can represent the intensity of the image and this is called the extraction of features represented the images. Features' extraction could be using statistical or spectral analysis.

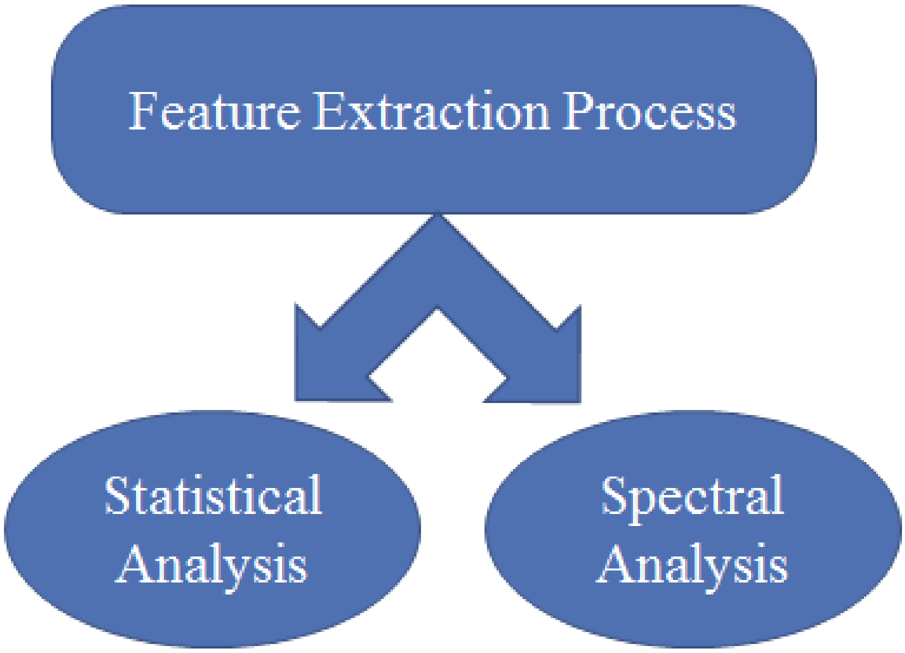

Figure 5.8: Two approaches of features' extraction.

5.2.1. Statistical Analysis on the Image

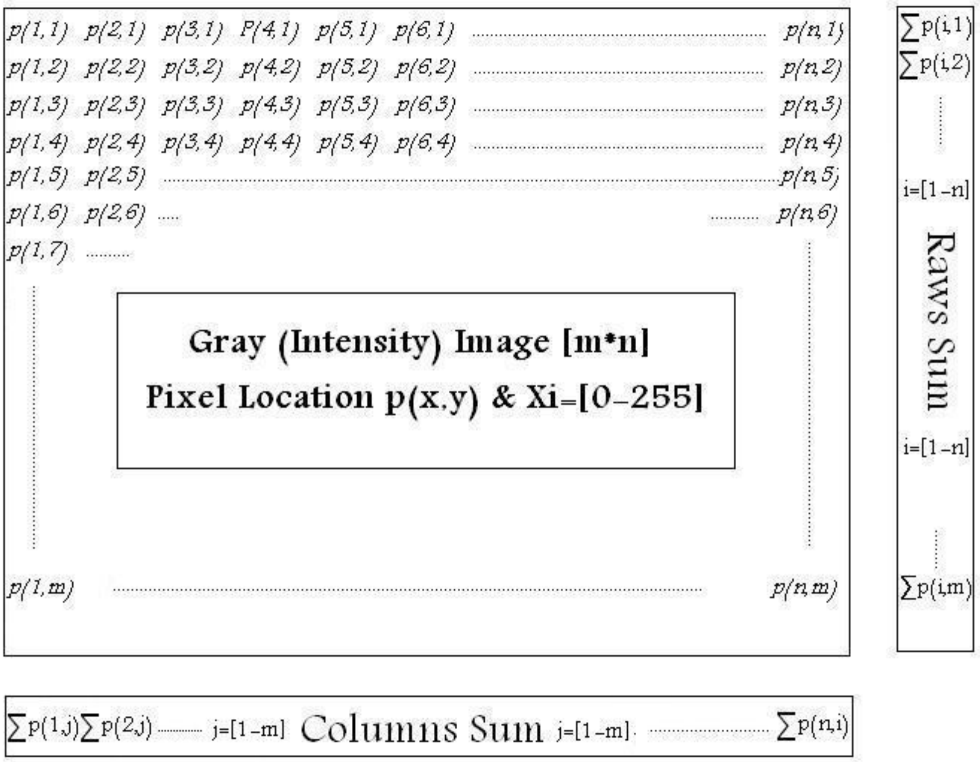

Figure 5.9: summation of Rows and Columns for 2-D image matrix.

Every Image contains pixels with values varies from 0 to 255. The lower half [0: 125] represents black places and the upper half represents white places [125; 255]. There is black board under the fabric so Yarn will be in the upper half and tends to 255, the space between yarns will be in the lower half and tens to 0, some defects will be in big area of high values and others will be in small area of low values. The main assumption is that the statistics of defect free images are similar. Statistical analysis shows the distribution of pixel values. There are first order, second order and higher order statistics. The first order statistics take place between individual pixel values and higher order statistics take place between two or more pixel values at locations with relative to each other. Because the yarn is not plastic and there is a tension, crimp, yarn hairiness and the fabric is not symmetrical. In addition, fabric take up produces noise in the image. Statistical analysis may get bad results because of all these parameters.

Three equations are used for statistical features' extraction:

1) The mean

$$\overline{x} = \frac{1}{n} \sum_{i=1}^{n} x_i \quad (1)$$

2) The summation of columns or rows

$$x = \sum_{i=1}^{n} x_i \quad (2)$$

3) The standard deviation

$$s = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} (x_i - \overline{x})^2} \quad (3)$$

5.2.1.1. Mean of Image

Calculate the average of pixels' values in the Image. This calculation uses two steps:

1) Calculating the average value in each column using equation (1). The result is a vector.
2) Calculating the average value of the resultant vector from step (1) using equation (1) also. The result is one value represents the average value of the image pixels' values.

This may show if there is defect or not.

5.2.1.2. Standard Deviation of the Summation of Rows

This calculation uses two steps:

1) Calculating the summation of each row using equation (2). The result is a vector.
2) Calculating the standard deviation of the resultant vector from step (1) using equation (3). The result is one represents the image.

5.2.1.3. Standard Deviation of the Summation of Columns

This calculation uses two steps:

1) Calculating the summation of each column using equation (2). The result is a vector.
2) Calculating the standard deviation of the resultant vector from step (1) using equation (3). The result is one represents the image.

5.2.2. Fourier Transform

Images can be defined by its' spatial location(x, y). The value of the function $f(x, y)$represents the intensity of the image at that point and that called the spatial domain. Fourier transform represents the function in the frequency domain instead of time domain. Frequency domain represents the image as a sum of complex exponentials of varying magnitudes, frequencies, and phases. The representation of the image at the frequency domain can clear any repeat at the image like repeats of woven fabric.

If $f(m, n)$is a function of two discrete spatial variables m and n, then the two-dimensional Fourier transform of $f(m, n)$ is defined by the relationship

$$F(w_1, w_2) = \sum_{m=-\infty}^{\infty} \sum_{n=-\infty}^{\infty} f(m, n)\ e^{-j\omega_1 m}\ e^{-j\omega_2 n}$$

The variables w_1 and $w_2$are frequency variables; their units are radians per sample. $F(w_1, w_2)$ is often called the frequency-domain representation of $f(m, n)$. $F(w_1, w_2)$ is a complex-valued function that is periodic both in w_1 and w_2, with period 2π . Because of the periodicity, usually only the range ($-\pi \leq w_1, w_2 \leq \pi$) is displayed. Where $F(0,0)$is the sum of all the values of$f(m, n)$. For this reason, $F(0,0)$ is often called the constant component or DC component of the Fourier transform. (DC stands for direct current). The inverse of a transform is an operation that when performed on a transformed image produces the original image. The inverse two-dimensional Fourier transform is given by

$$f(m, n) = \frac{1}{4\pi^2} \int_{w_1=-\pi}^{\pi} \int_{w_2=-\pi}^{\pi} F(w_1, w_2)\, e^{j\omega_1 m}\, e^{j\omega_2 n} \quad dw_1 dw_2$$

This equation means that $f(m, n)$ can be represented as a sum of an infinite number of complex exponentials (sinusoids) with different frequencies. The magnitude and phase of the contribution at the frequencies (w_1, w_2) are given by $F(w_1, w_2)$ [42].

By applying the frequency domain a spectrum can be obtained with defined peaks that represent frequencies in the image. The following figures show the 2-D and the 3-D representation of the Fourier spectrum of a woven fabric image.

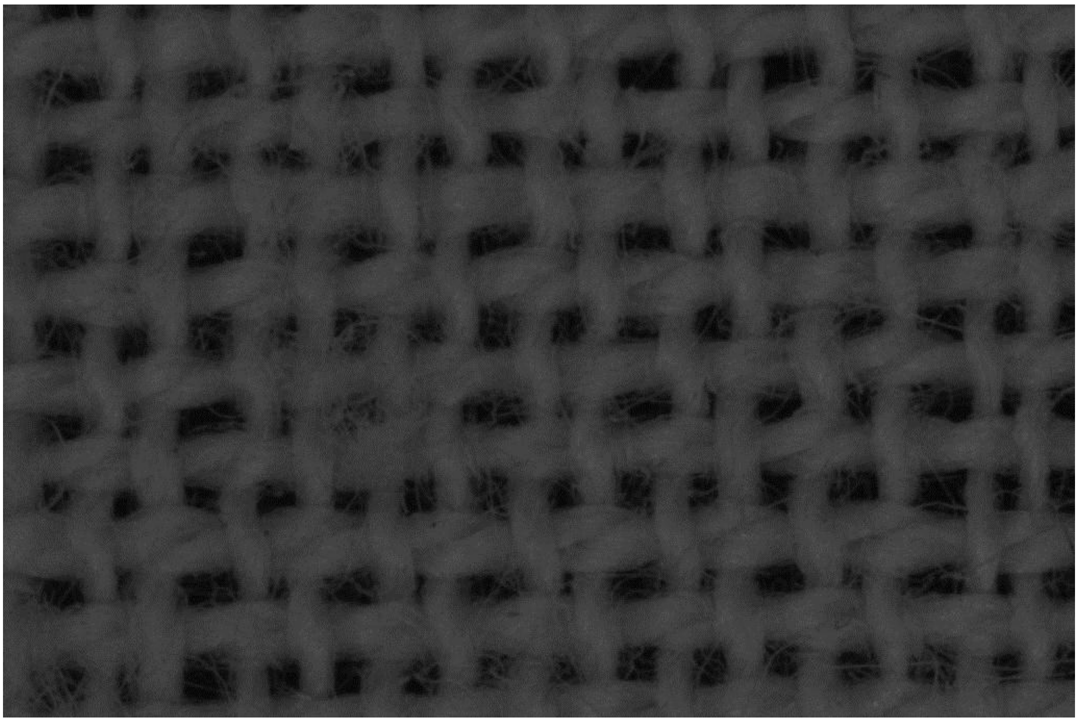

Figure 5.10: a woven fabric image.

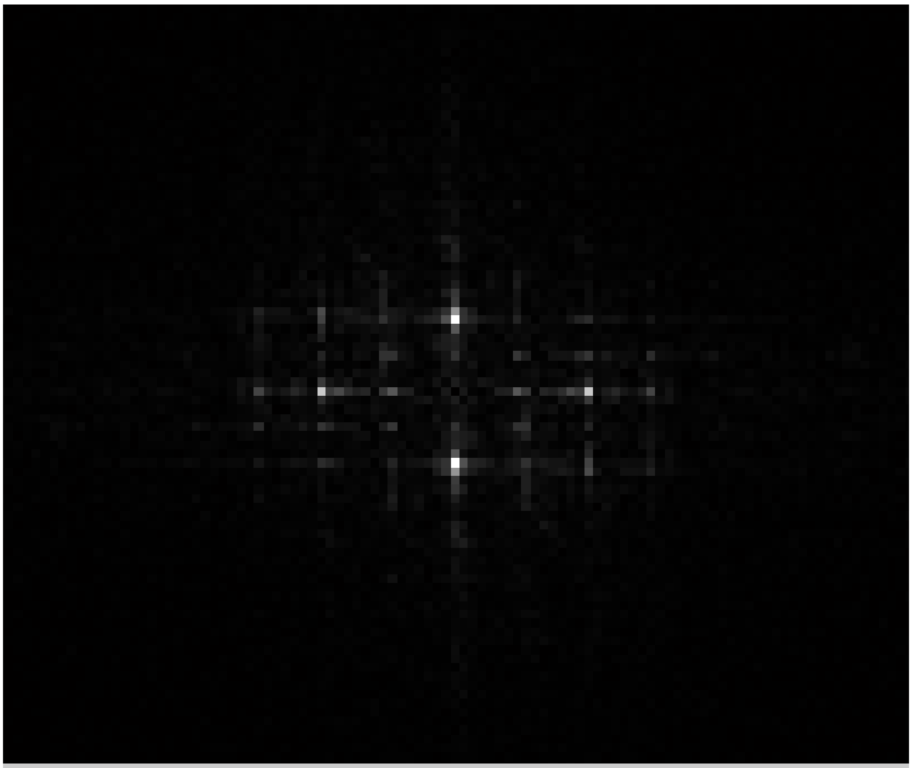

Figure 5.11: the 2-D representation of the Fourier spectrum of image in figure (5.9).

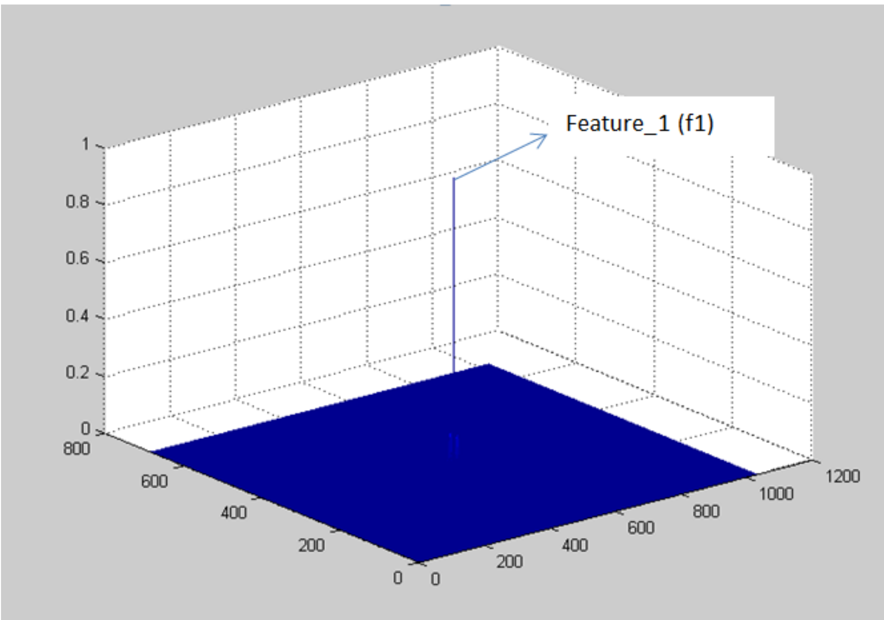

Figure 5.12: the 3-D representation of the Fourier spectrum of image in figure (5.9).

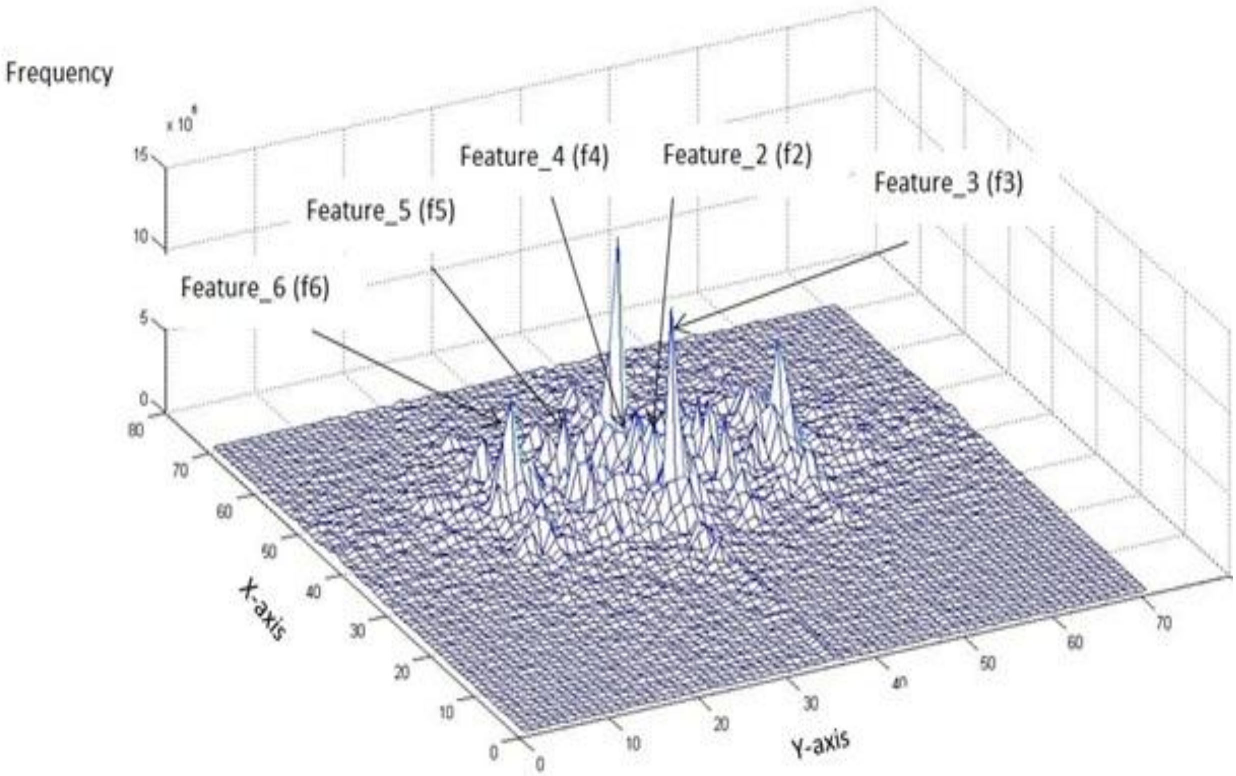

Figure 5.13: the 3-D representation of the Fourier spectrum of image in figure (5.9) after removing the central peak.

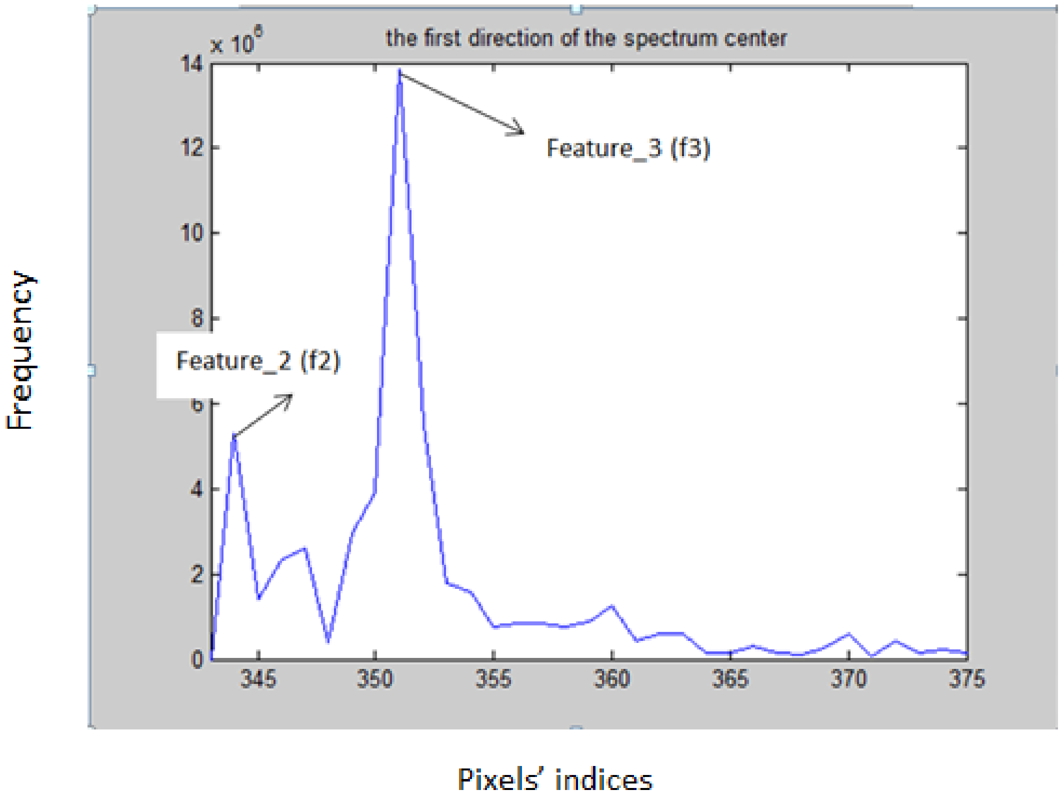

Figure 5.14: the x-direction of the Fourier spectrum of image in figure (5.9) ranged from the center to 375.

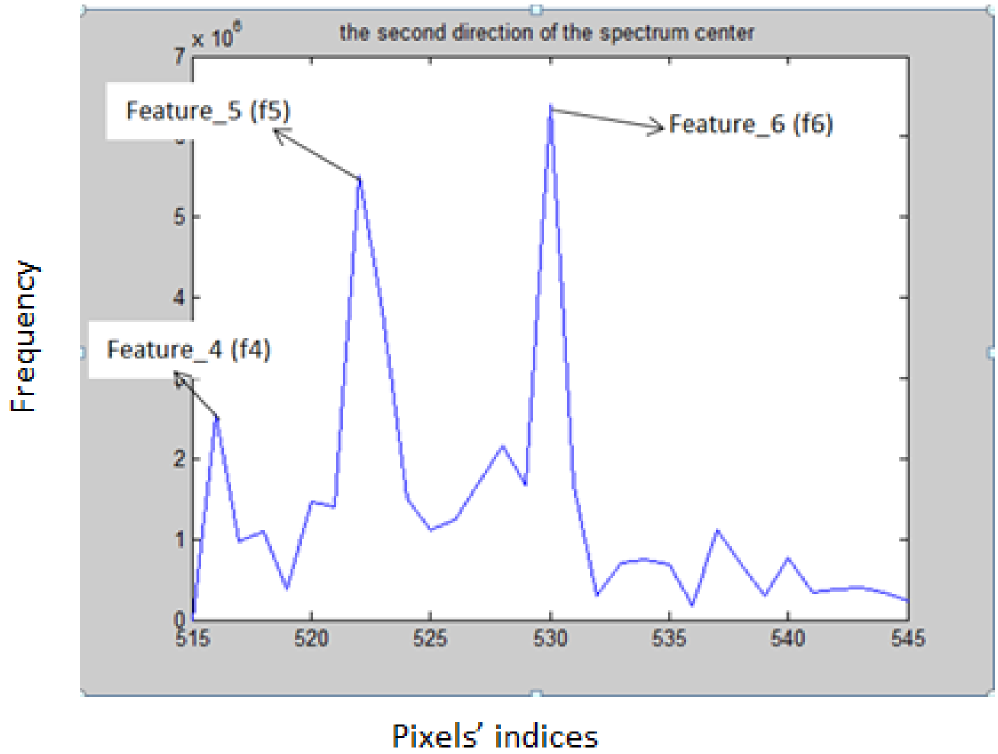

Figure 5.15: the y-direction of the Fourier spectrum of image in figure (5.9) ranged from the center to 545.

A program had been built to show the domain that the peaks locate in for each defect. The program showed that the peaks located in 30 pixel ranges in both directions; the x-Direction and y-Direction. The program had been run on these ranges. In x-Direction there were two peaks could be extracted as features. In y-Direction there were three peaks that could be extracted as features as well. The following tables show the result of running the program on 10 images for each defect and the location of each peak founded in the Fourier spectrum in both directions.

Table 5.1: The location of Fourier spectrum peaks for Defect free.

No		X-Direction			Y-Direction		
		peak_1	peak_2		peak_1	peak_2	peak_3
1	defect free		9		8	16	
2			9		8	16	
3			9		8	16	
4			9		8	16	
5			9		8	16	
6			9		8	16	
7			9		8	16	
8			9		8	15	
9			9		8	16	
10			9		8	15	

Table 5.2: The location of Fourier spectrum peaks for Float warp.

No		X-Direction			Y-Direction		
		peak_1	peak_2		peak_1	peak_2	peak_3
1	Float warp		9		8	16	
2			9			16	
3			9			16	
4			9			16	
5			9			16	
6			9		8	16	
7			9		8	16	
8			9			16	
9			9		8	16	
10			9		8	16	

Table 5.3: The location of Fourier spectrum peaks for Light beat.

No		X-Direction			Y-Direction		
		peak_1	peak_2		peak_1	peak_2	peak_3
1	Light beat		6		8		
2			6		8	16	
3			8		8	16	
4			7		9	16	
5			5		8		
6			8		8	16	
7		2	6		8	16	
8			8		8	16	
9			7		8	16	
10					8	16	

Table 5.4: The location of Fourier spectrum peaks for Heavy beat.

No		X-Direction			Y-Direction		
		peak_1	peak_2		peak_1	peak_2	peak_3
1	Heavy beat		9		8	16	
2		9	11			16	
3		8	10			16	
4			10			16	
5			9		8	16	
6		8	10			16	
7			9		14	16	
8			10		8	16	
9			11		9	16	
10			11			16	

Table 5.5: The location of Fourier spectrum peaks for Missing pick.

No		X-Direction			Y-Direction		
		peak_1	peak_2		peak_1	peak_2	peak_3
1	Missing picks	2			6	8	
2		3			8	10	
3		2				16	
4		2	4			16	
5		3			8	16	
6		2				16	
7		2	4		8	15	
8		2			8		
9		2				15	
10		2	5		10		

Table 5.6: The location of Fourier spectrum peaks for Double end.

No		X-Direction			Y-Direction		
		peak_1	peak_2		peak_1	peak_2	peak_3
1	Double end	3	9			15	
2			9		10	16	
3		9	11		8	15	
4		7	9		9	16	
5			9		10	14	
6			9			16	
7			9			16	
8			9		9	16	
9			9			16	
10			9		8	15	

Table 5.7: The location of Fourier spectrum peaks for Hole.

No		X-Direction			Y-Direction		
		peak_1	peak_2		peak_1	peak_2	peak_3
1	Hole	4	6			15	
2			9			16	
3			9			16	
4			9			16	
5			9			16	
6		2	9		3	16	
7		3	9		2	8	16
8			9		3	16	
9		2	9		3	16	
10			9		3		

Table 5.8: The location of Fourier spectrum peaks for Stain

No		X-Direction			Y-Direction		
		peak_1	peak_2		peak_1	peak_2	peak_3
1	Stain	2	9			16	
2			9		2	16	
3			9			16	
4			9			16	
5			9		2	16	
6			9		2	16	
7			9			16	
8			9			16	
9			9		2	16	
10			9		2	16	

Table 5.9: The location of Fourier spectrum peaks for Double pick.

No		X-Direction			Y-Direction		
		peak_1	peak_2		peak_1	peak_2	peak_3
1	Double pick		8		8	16	
2		3	7		8	16	
3		3	7		8	16	
4			8		8	16	
5			7		8	16	
6			8		9	16	
7			9		9	16	
8			8		8	16	
9		4	6		8	16	
10			8		8	16	

Table 5.10: The location of Fourier spectrum peaks for Knot.

No		X-Direction			Y-Direction		
		peak_1	peak_2		peak_1	peak_2	peak_3
1	Knot	2	9			16	
2			8			16	
3			9			16	
4		6	9			15	
5		4	9			16	
6		2	9			12	
7			9		9	16	
8			9			16	
9			9			16	
10			9			16	

Table 5.11: The location of Fourier spectrum peaks for big knot.

No		X-Direction			Y-Direction		
		peak_1	peak_2		peak_1	peak_2	peak_3
1	Big knot		9		2	16	
2		2	9		2	16	
3		2				16	
4		2	10		2	8	16
5		2	10		2		
6		2	9		2		
7		2	10		8	16	
8		2	9		2	16	
9		2			2	4	
10		2	10		2	16	

The features extracted from Fourier spectrum are the magnitudes of the cleared peaks at the center lines of the spectrum at both directions. Five features are extracted as following:

Table 5.12: The features extracted from Fourier spectrum.

No. of feature	Peak spatial range	Feature figure
Feature_1 (f1)	The maximum peak shown at the center of the spectrum that represents the average value of the image.	Figure (5.12)
Feature_2(f2)	The maximum peak of the center line at x-direction ranges from [344: 348].	Figure (5.14)
Feature_3(f3)	The maximum peak of the center line at x-direction ranges from [349: 355].	Figure (5.14)
Feature_4 (f4)	The maximum peak of the center line at x-direction ranges from [516: 520].	Figure (5.15)
Feature_5 (f5)	The maximum peak of the center line at y-direction ranges from [521: 525].	Figure (5.15)
Feature_6 (f6)	The maximum peak of the center line at y-direction ranges from [528: 532].	Figure (5.15)

CHAPTER 6

IMAGE CLASSIFICATION

Chapter 6

Image Classification

6.1. Artificial neural network

An artificial neural network is a mathematical model which mimics a biological neural network. A neural network consists of an interconnected group of artificial neurons, and it processes information using an approach of connection. Neural networks are used for modeling complex relationships between inputs and outputs or to find patterns in data. Artificial neural network can perform several tasks such as: Classification, Pattern recognition; feature extraction, image matching and Prediction. Figure (6.1) shows a simple network with neurons in the input, hidden and the output layers.

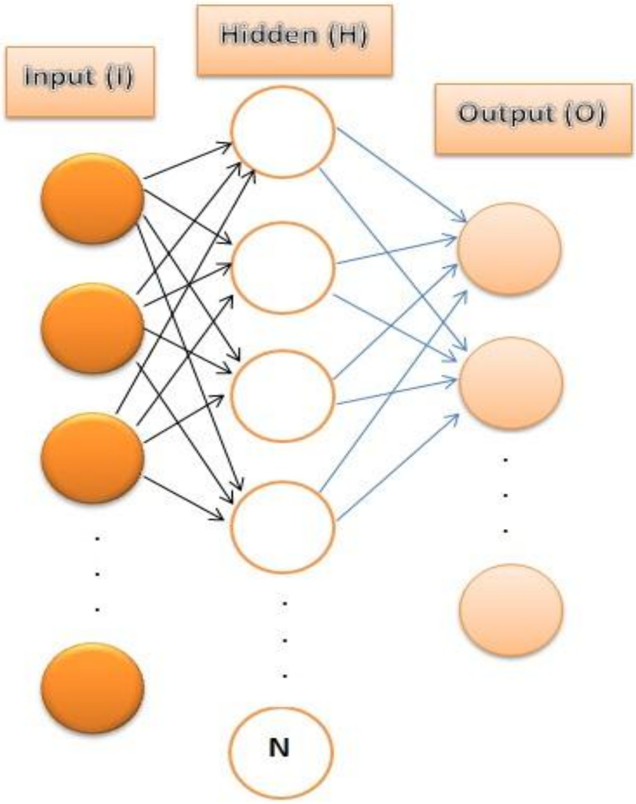

Figure 6.1: a simple neural network

6.2. Network function (Transfer function)

Mathematically, a neuron's network function $f(x)$n is defined as a composition of other functions$g_i(x)$, which can further be defined as a composition of other functions. This can be conveniently represented as a network structure, with arrows depicting the dependencies between variables. A widely used type of composition is the nonlinear weighted sum, where $f(x) = \sum_i \; w_i \, g_i(x)$, where k (commonly referred to as the activation function) is some predefined function, such as the hyperbolic tangent. It will be convenient for the following to refer to a collection of functions $g_i$as simply a vector $g(g_1, g_{2,\ldots\ldots\ldots} g_{n,})$ [43].

Figure (6.2) illustrates the linear transfer function.

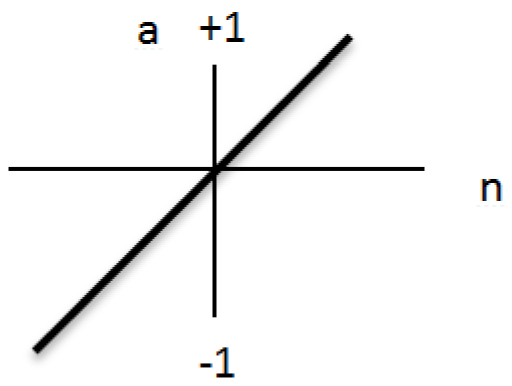

Figure 6.2: linear Transfer Function

The sigmoid transfer function shown below takes the input, which can have any value between plus and minus infinity, and squashes the output into the range 0 to 1.

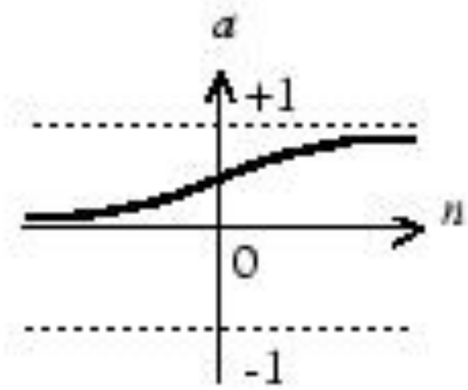

Figure 6.3: Log-Sigmoid Transfer Function

The majority of Neural Networks use sigmoid functions in the hidden layers of multilayer networks, in part because it is differentiable.

Artificial neural network composed of many neurons that co-operate to perform the desired function. Neurons can be combined in a layer, and a particular network could contain one or more such layers.

1. One Layer of Neurons
2. Multiple Layers of Neurons

In our work the sigmoid function was used as a transfer function in a multi-layer network that contained two hidden layers. Each layer consists of 25 neurons.

CHAPTER 7

RESULTS AND DISCUSSIONS

Chapter 7

Results and Discussions

7.1. Classification of all defects in one step

7.1.1. Using statistical features only

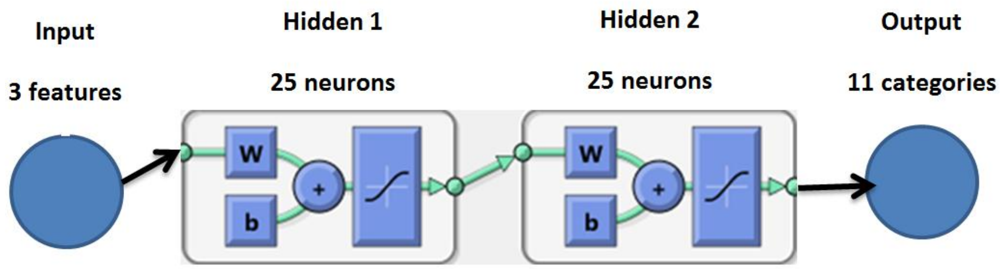

Figure 7.1: NNT uses statistical features.

Table 7.1: Classification's result of NNT uses statistical features only.

No	defect category	No. of images	Right classification	Wrong classification	% classification
1	Knot	10	7	2_Hole, 1_Double pick	70
2	Float warp	10	7	2_Double end, 1_Hole	70
3	Light beat	10	10	_	100
4	Heavy beat	10	8	1_Knot, 1_Defect free	80
5	Missing Picks	10	10	_	100
6	Double end	10	9	1_Defect free	90
7	Hole	10	9	1_Double end	90
8	Stain	10	9	1_Double end	90
9	Double pick	10	6	1_Knot , 3_Defect free	60
10	Defect free	10	9	1_Double pick	90
11	Big knot	10	9	1_Light beat	90
	Overall performance (%)				84.5

7.1.2. Using spectral features only

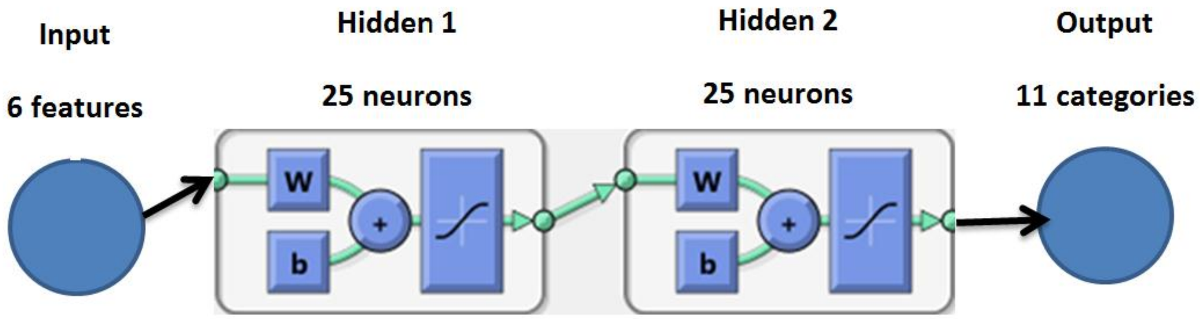

Figure 7.2: NNT uses spectral features.

Table 7.2: Classification's result of NNT uses spectral features only.

No	defect category	No. of images	Right classification	Wrong classification	% classification
1	Knot	10	8	2_Double end	80
2	Float warp	10	9	1_Double end	90
3	Light beat	10	10	_	100
4	Heavy beat	10	9	1_Double pick	90
5	Missing Picks	10	10	_	100
6	Double end	10	10	_	100
7	Hole	10	10	_	100
8	Stain	10	9	1_Hole	90
9	Double pick	10	8	1_Heavy beat, 1_Defect free	80
10	Defect free	10	9	1_Heavy beat	90
11	Big knot	10	10	_	100
	Overall performance (%)				92.7

7.1.3. Using statistical features and spectral features

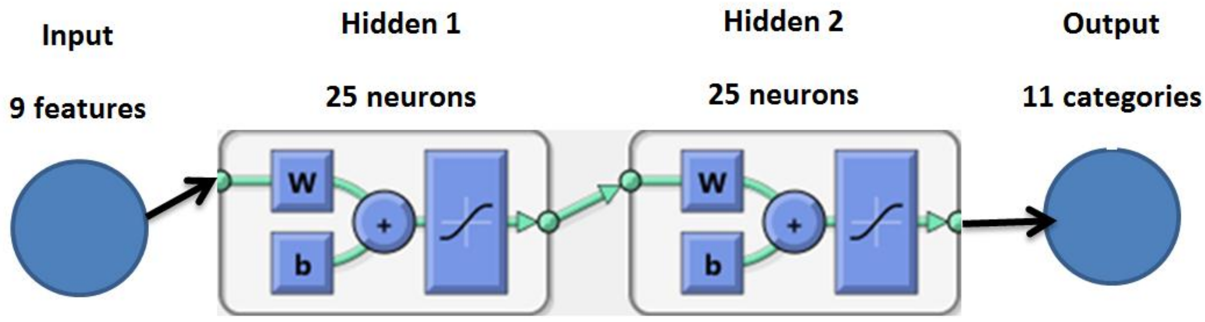

Figure 7.3: NNT uses statistical and spectral features.

Table 7.3: Classification's results of NNT uses statistical features and spectral features.

No	defect category	No.of images	Right classification	Wrong classification	% classification
1	Knot	10	10	_	100
2	Float warp	10	9	1_Hole	90
3	Light beat	10	10	_	100
4	Heavy beat	10	9	1_Double pick	90
5	Missing Picks	10	10	_	100
6	Double end	10	10	_	100
7	Hole	10	9	1_Defect free	90
8	Stain	10	10	_	100
9	Double pick	10	10	_	100
10	Defect free	10	10	_	100
11	Big knot	10	10	_	100
	Overall performance (%)				97.3

The results of the above three tables show that the classification using Fourier features only get better results than using statistical features only for classifications while using both types of features; statistical and spectral get the best results.

7.2. Classification of defects in three step

7.2.1. Defect or defect free

7.2.1.1. Using statistical features only

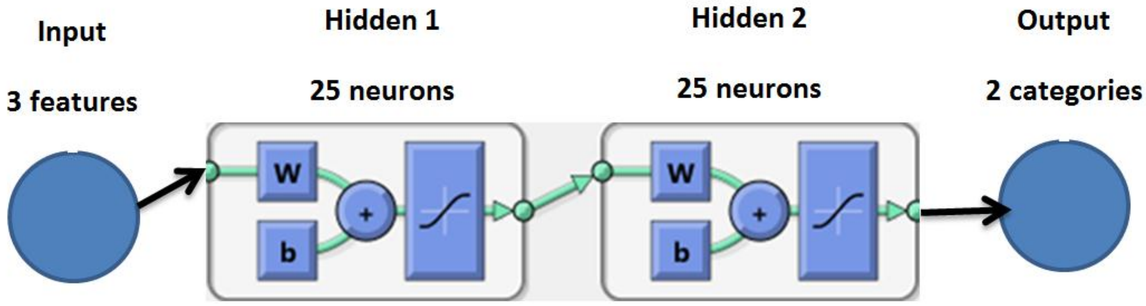

Figure 7.4: NNT uses statistical features.

Table 7.4: Classification's results of NNT uses statistical features only.

No	defect category	No.of images	Right classification	Wrong classification	% classification
1	defect free	50	47	3 defect	94
2	defect	50	44	6 free	88
	Overall performance (%)				91

7.2.1.2. Using spectral features only

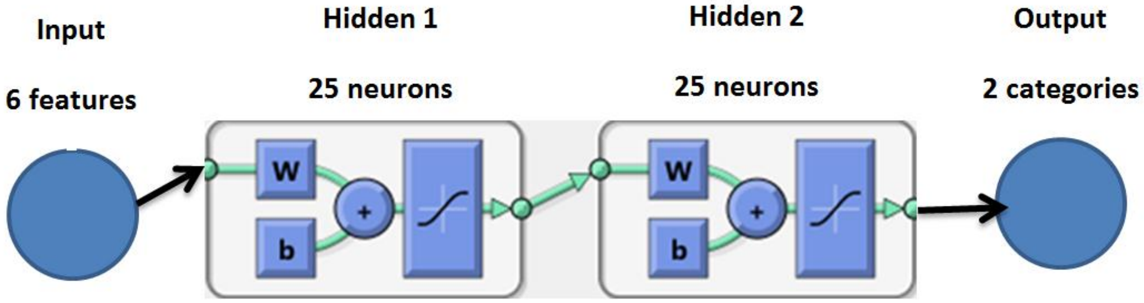

Figure 7.5: NNT uses spectral features.

Table 7.5: Classification's results of NNT uses spectral features only.

No	defect category	No.of images	Right classification	Wrong classification	% classification
1	defect free	50	47	3 defect	94
2	defect	50	42	8 free	84
	Overall performance (%)				89

7.2.1.3. Using statistical features and spectral features

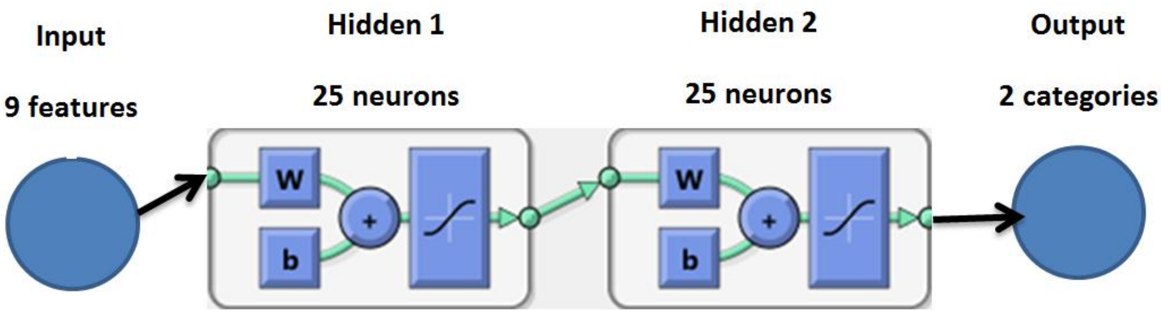

Figure 7.6: NNT uses statistical and spectral features.

Table 7.6: Classification's results of NNT uses statistical features and spectral features.

No	defect category	No.of images	Right classification	Wrong classification	% classification
1	defect free	50	44	6 defect	88
2	defect	50	43	7 free	86
	Overall performance (%)				87

The results listed in above three tables show that the classification using Fourier features only get better results than using both types of features; statistical and spectral for classifications while using statistical features only get the best results.

7.2.2. Area, Warp or Weft

7.2.2.1. Using statistical features only

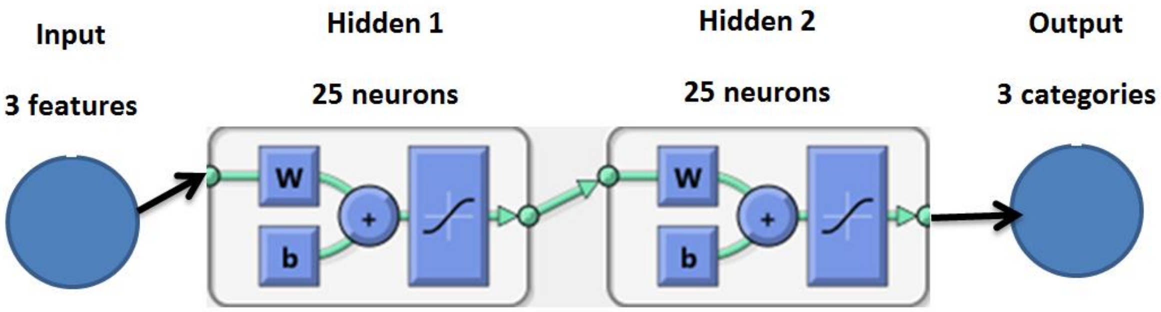

Figure 7.7: NNT uses statistical features.

Table 7.7: Classification's results of NNT uses statistical features.

No	defect category	No.of images	Right classification	Wrong classification	% classificatio n
1	area	50	43	4 warp ,3 weft	86
2	warp	50	42	8 area	84
3	weft	50	49	1 area	98
	Overall performance (%)				89.3

7.2.2.2. Using spectral features only

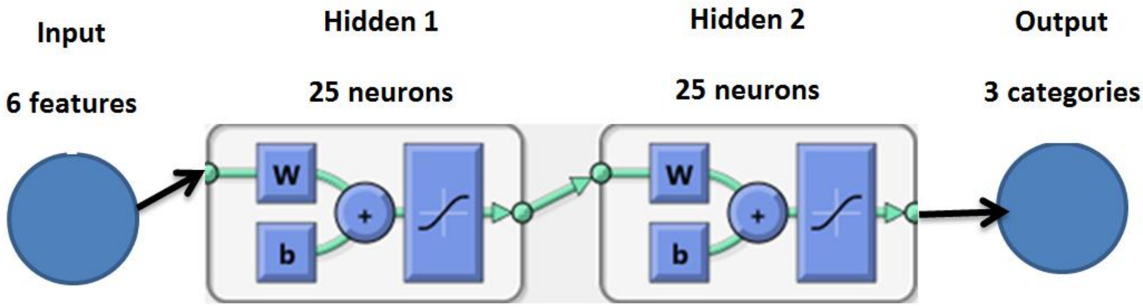

Figure 7.8: NNT uses spectral features.

Table 7.8: Classification's results of NNT uses spectral features only.

No	defect category	No.of images	Right classification	Wrong classification	% classification
1	area	50	47	3 warp	94
2	warp	50	50	_	100
3	weft	50	46	4 area	92
	Overall performance (%)				95.3

7.2.2.3. Using statistical features and spectral features

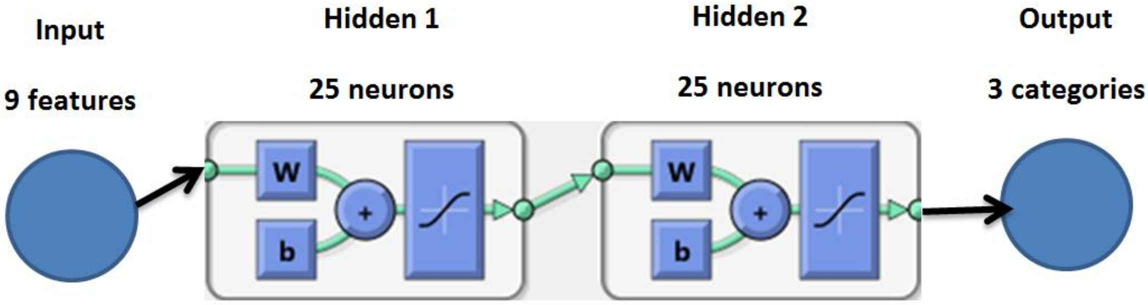

Figure 7.9: NNT uses statistical and spectral features.

Table 7.9: Classification's results of NNT uses statistical features and spectral features.

No	defect category	No.of images	Right classification	Wrong classification	% classification
1	area	50	45	4 warp , 1 weft	90
2	warp	50	49	1 area	98
3	weft	50	48	2 area	96
	Overall performance (%)				94.7

The results listed in above three tables show that the classification using Fourier features only get better results than using statistical features only for classifications while using both types of features; statistical and spectral get the best results.

7.2.3. Area defects

7.2.3.1. Using statistical features only

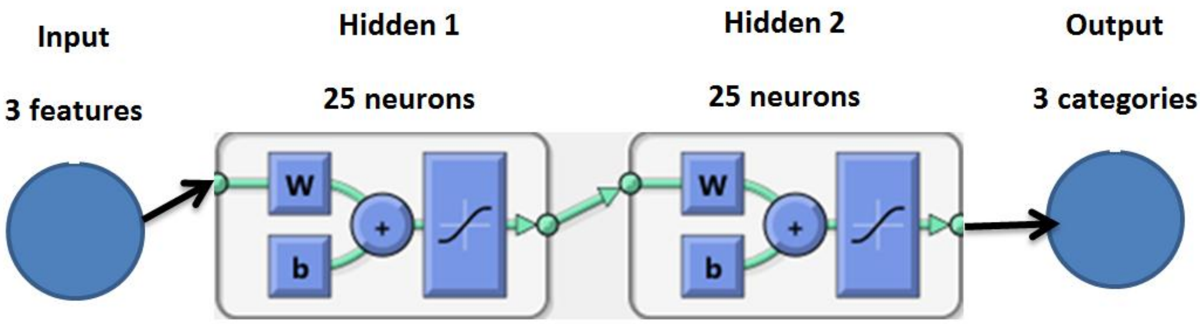

Figure 7.10: NNT uses statistical features.

Table 7.10: Classification's results of NNT uses statistical features only.

No	defect category	No.of images	Right classification	Wrong classification	% classification
1	Knot	10	9	1 hole	90
2	hole	10	8	2 knot	80
3	stain	10	10	_	100
	Overall performance (%)				90

7.2.3.2. Using spectral features only

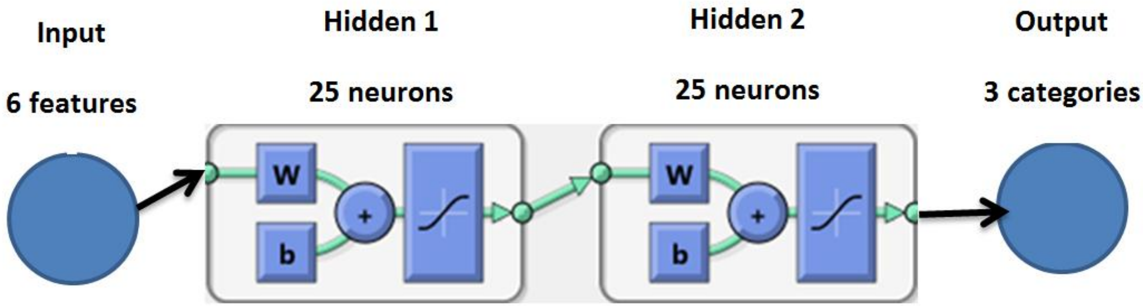

Figure 7.11: NNT uses spectral features.

Table 7.11: Classification's results of NNT uses spectral features only.

No	defect category	No.of images	Right classification	Wrong classification	% classification
1	Knot	10	10	_	100
2	hole	10	8	2 knot	80
3	stain	10	10	_	100
	Overall performance (%)				93.3

7.2.3.3. Using statistical features and spectral features

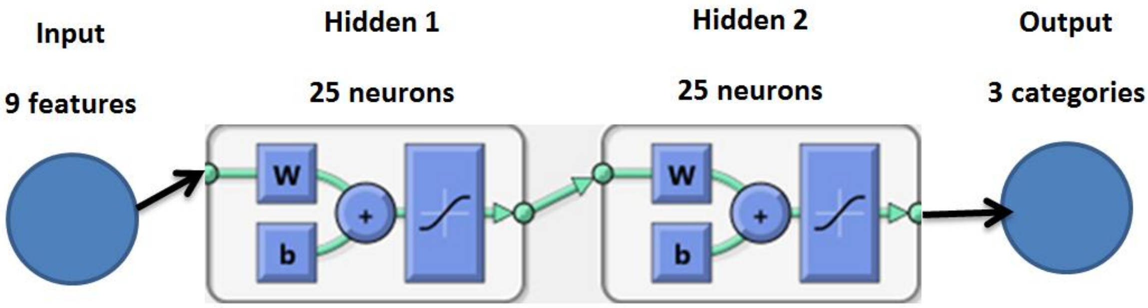

Figure 7.12: NNT uses statistical and spectral features.

Table 7.12: Classification's results of NNT uses statistical features and spectral features.

No	defect category	No.of images	Right classification	Wrong classification	% classification
1	Knot	10	10	_	100
2	hole	10	10	_	100
3	stain	10	10	_	100
	Overall performance (%)				100

The results listed in above three tables show that the classification using Fourier features only get better results than using statistical features only for classifications while using both types of features; statistical and spectral get the best results.

7.2.4. Warp defects

7.2.4.1. Using statistical features only

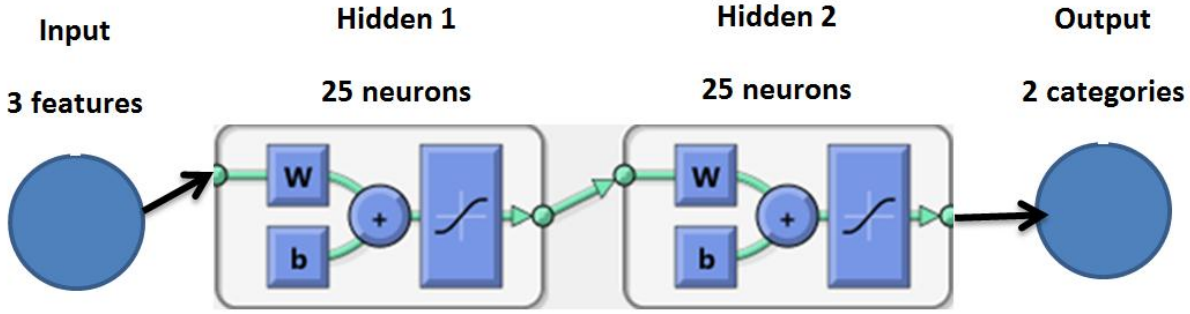

Figure 7.13: NNT uses statistical features.

Table 7.13: Classification's results of NNT uses statistical features only.

No	defect category	No.of images	Right classification	Wrong classification	% classification
1	Double end	10	10	_	100
2	float warp	10	10	_	100
	Overall performance (%)				100

7.2.4.2. Using spectral features only

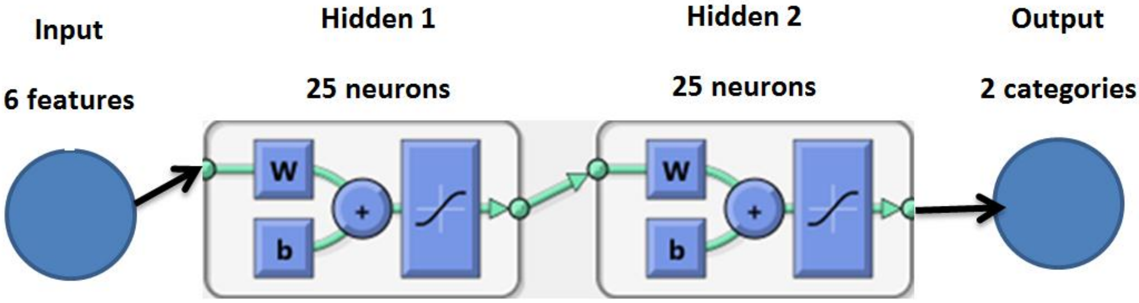

Figure 7.14: NNT uses spectral features.

Table 7.14: Classification's results of NNT uses spectral features only.

No	defect category	No.of images	Right classification	Wrong classification	% classification
1	Double end	10	9	1_float warp	90
2	Float warp	10	10	_	100
	Overall performance (%)				95

7.2.4.3. Using statistical features and spectral features

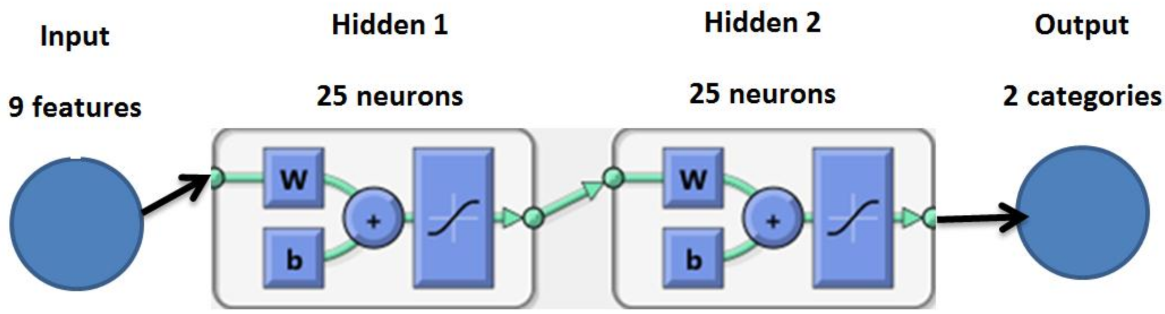

Figure 7.15: NNT uses statistical and spectral features.

Table 7.15: Classification's results of NNT uses statistical features and spectral features.

No	defect category	No.of images	Right classification	Wrong classification	% classification
1	Double end	10	10	_	100
2	Float warp	10	10	_	100
	Overall performance (%)				100

The results listed in above three tables show that the classification using Fourier features only get the worst results while using statistical features only for classifications get similar results as using both types of features; statistical and spectral get the best results. Using statistical features only is better because it uses only three features while using both types of features uses nine features that can decrease the speed of classification.

7.2.5. Weft defects

7.2.5.1. Using statistical features only

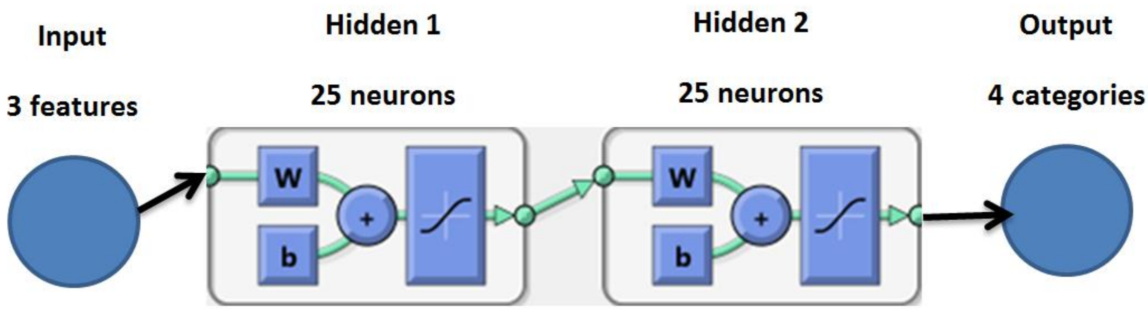

Figure 7.16: NNT uses statistical features.

Table 7.16: Classification's results of NNT uses statistical features only.

No	defect category	No. of images	Right classification	Wrong classification	% classification
1	Light beat	10	10	_	100
2	Heavy beat	10	10	_	100
3	Missing Picks	10	10	_	100
4	Double pick	10	10	_	60
	Overall performance (%)				100

7.2.5.2. Using spectral features only

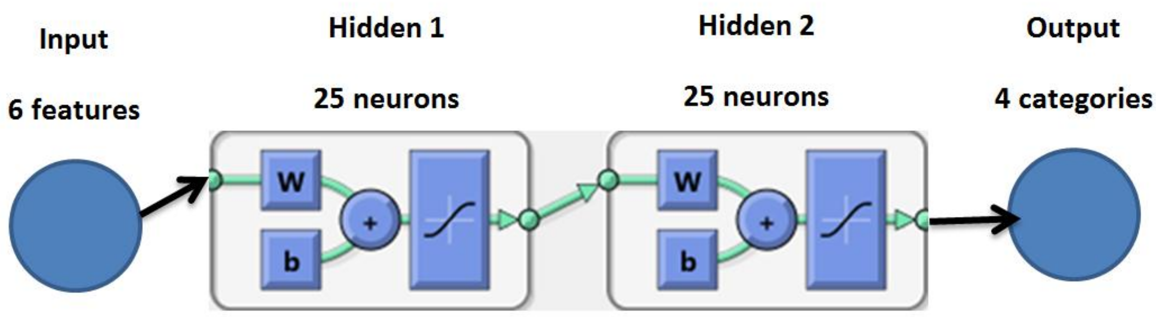

Figure 7.17: NNT uses spectral features.

Table 7.17: Classification's results of NNT uses spectral features only.

No	defect category	No. of images	Right classification	Wrong classification	% classification
1	Light beat	10	10	_	100
2	Heavy beat	10	10	_	100
3	Missing Picks	10	10	_	100
4	Double pick	10	10	_	100
	Overall performance (%)				100

7.2.5.3. Using statistical features and spectral features

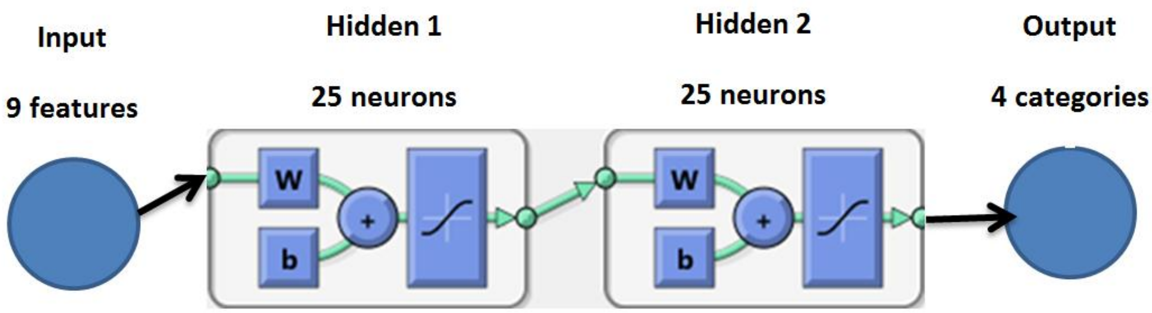

Figure 7.18: NNT uses statistical and spectral features.

Table 7.18: Classification's results of NNT uses statistical features and spectral features.

No	defect category	No. of images	Right classification	Wrong classification	% classification
1	Light beat	10	10	_	100
2	Heavy beat	10	10	_	100
3	Missing Picks	10	10	_	100
4	Double pick	10	10	_	100
	Overall performance (%)				100

The results listed in above three tables show that the classification using Fourier features only, statistical features only or both types of features; statistical and spectral get similar results. Using statistical features only is the best way for weft defects' classification as it uses only three features that might use the least time.

7.3. GUI program

To run program Press load button in figure (7.19), then visible figure (7.20), choose image and press open will get the result in figure (7.21).

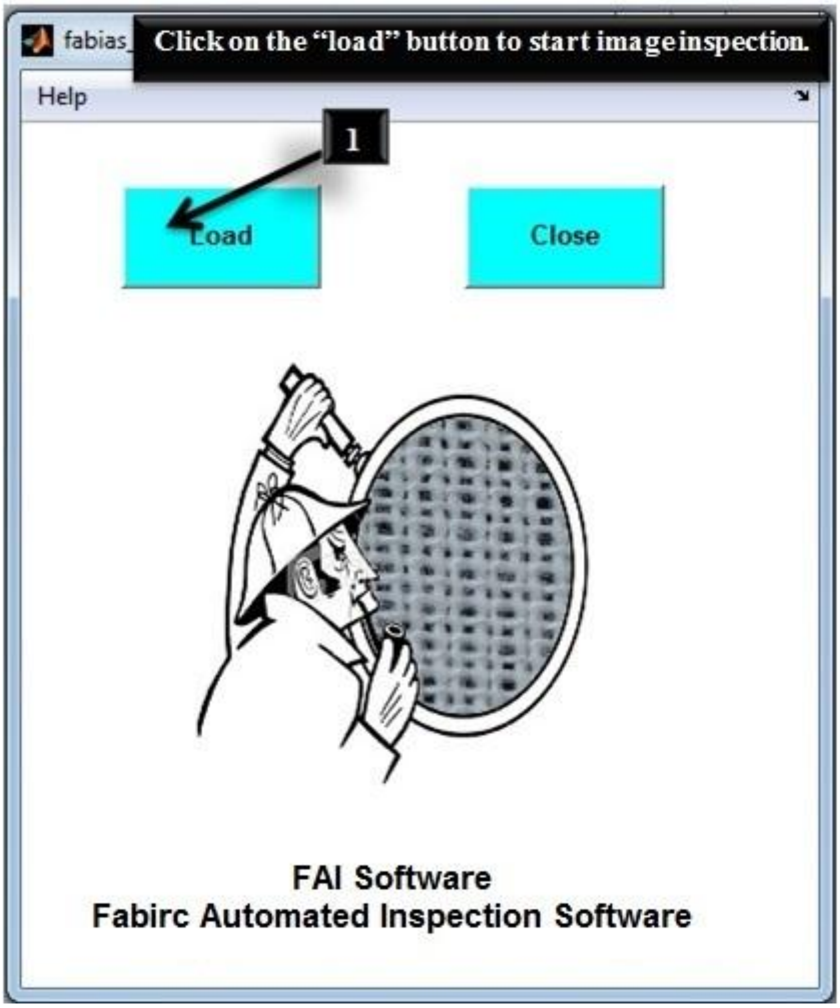

Figure 7.19: first screen.

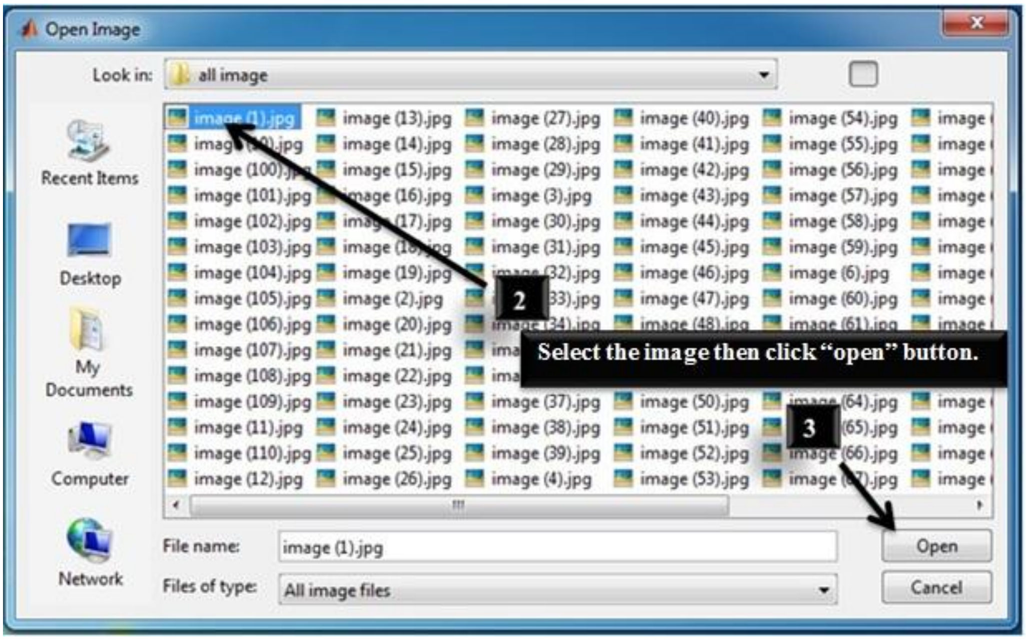

Figure 7.20: second screen.

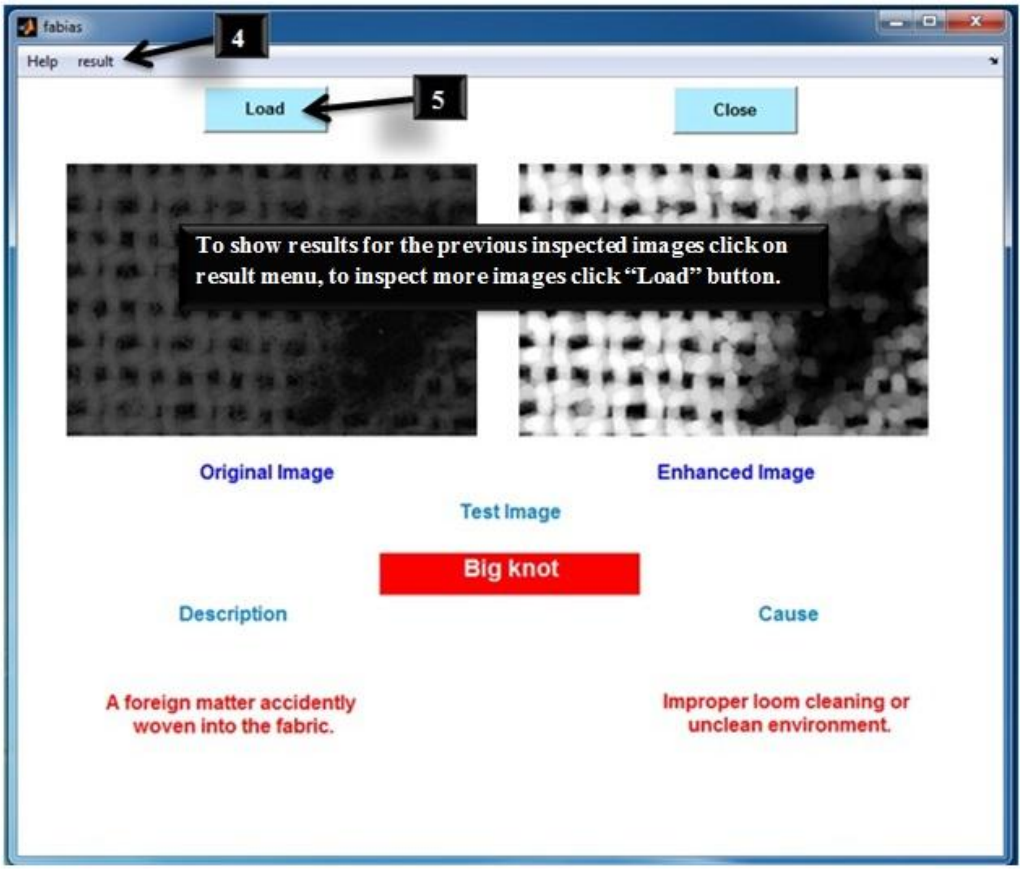

Figure 7.21: third screen.

CHAPTER 8

CONCLUSION AND FUTURE WORK

Chapter 8

Conclusion and future work

8.1. Conclusion

This work utilizes a digital camera to acquire and transmit fabric images to a computer which enhances and extracts the features for each image. Then, the features are processed using Artificial Intelligence technique to detect and classify if the fabric has a defect or not and classify 10 fabric defects. Two approaches have been used for classification using statistical features only, spectral features only or both statistical and spectral. The first approach classifies all the defects in one step. The results show that using both statistical and spectral features with each other give a 97.3% correct classification. The second approach classifies the defect on three steps. The first step classifies if the fabric sample has a defect or free defect. The results show that statistical features get the best classification with the least time with 91% percentage. The second step classifies the direction of the defect; Area, Warp or weft. The use of both features results a 97.3% classification rate. The third step classifies the defect. For the area defects Fourier features get a 100% classification. While using statistical features results a 100% correct classification for warp and weft defects with lower time.

8.2. Future work

A video analysis will be applied for fabric faults inspection with the help of mechanical system. An inspection machine will be built for fabric rollers, camera and light system movement. The proposed system will be automatically inspected manufactured fabric. The defects will be recorded in a database and providing a report including the frequent defects to fix their sources. Applying such automatic system in weaving mills will increase the profit and the product quality.

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APPENDIXES

Appendixes

Image divided into nine small images

```
image=rgb2gray(imread(imgetfile));
[x,y]=size(image);
image1=image( 1    : x/3 ,   1      :   y/3);
image2=image( 1    : x/3 ,   y/3:   2*y/3);
image3=image( 1    : x/3 ,   2*y/3  :   y);
image4=image( x/3 : 2*x/3   ,   1      :   y/3);
image5=image( x/3 : 2*x/3   ,   y/3   :   2*y/3);
image6=image( x/3 : 2*x/3   ,   2*y/3   :   y);
image7=image( 2*x/3 : x   ,   1      :   y/3);
image8=image( 2*x/3 : x   ,   y/3   :   2*y/3);
image9=image( 2*x/3 : x   ,   2*y/3   :   y);
imwrite(image1,('image1.jpg'));
imwrite(image2,('image2.jpg'));
imwrite(image3,('image3.jpg'));
imwrite(image4,('image4.jpg'));
imwrite(image5,('image5.jpg'));
imwrite(image6,('image6.jpg'));
imwrite(image7,('image7.jpg'));
imwrite(image8,('image8.jpg'));
imwrite(image9,('image9.jpg'));
```

Images enhancement:

```
function [Image]=enhancement(image)
background = imopen(im,strel('disk',12));
image1=image-background;
Image= imadjust(image1);
```

Statistical features' extraction:

```
function feature=feature statistical(image)
feature(1) =mean (mean (image));
feature(2) =std (sum (image));
feature(3) =std (sum (image'));
```

Fourier features' extraction:

```
Function feature=feature fourier(image)
k=[344 348 349 355 516 520 521 525 528 532 ];
image=abs(fftshift(fft2(image)));
[x,y]=size(image);
feature (1)=max(max(image));
image-dr1=image(:,(y/2));
image-dr2=image((x/2),:);
feature (2) =max(image-dr1(k(1):k(2)));
feature (3) =max(image-dr1(k(3):k(4)));
```

```
feature (4)=max(image-dr2(k(5):k(6)));
feature (5)=max(image-dr2(k(7):k(8)));
feature (6)=max(image-dr2(k(9):k(10)));
```

Matlab code for classification using statistical features only:

First approach

```
clear
clc
t=0;
target=[];
no_folders=11;
no_images=10;
for no_folder=1:no_folders
for no_image_loop =1:no_images
image=imread(strcat(image,int2str(no_folder),'\1 (',int2str(no_image_loop),').JPG' ));
image=enhansment(image);
feature=feature_statistical(image);
t=t+1;
feature(t,:)=feature;
tt=zeros(no_folders,no_images);
tt(no_folder,:)=1;
end
target=[target tt];
end
input=feature';
net = patternnet([25 25],'trainrp');
net = train(net,input,target);
outputs = net(input);
 plotconfusion(target,outputs)
```

Second approach

```
% --- Executes on button press in classification_S.
function calssification_S_Callback(hObject, eventdata, handles)
% hObject    handle to defect_or_free_S (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)
close all
clear
clc
% number folders
End folder=input('number folders = ');
number folder=end folder;
tt=0;
targets=[];
for no folder=1:end_folder
% number of images
```

```
   No image = input(strcat('number image folder ',int2str(no folder) ,'='));
for no image loop = 1:no_image
         % read image
im=imread(strcat(image,int2str(no folder),'\1 (',int2str(no image loop),').JPG'));
% enhansment image
[im]=enhansment(im);
% feature extraction
feature=feature statistical(im);
tt=tt+1;
inputs(:,tt)=feature;
t=zeros(number folder,no image);
t(no_folder,:)=1;
end
targets=[targets t];
end
 save('targets_inputs.mat','targets','inputs');
```

Matlab code for classification using Fourier features only:

First approach

```
Clear
clc
t=0;
target=[];
no folders=11;
no images=10;
for no folder=1:no folders
for no image loop =1:no_images
a=imread(strcat(image,int2str(no_folder),'\1 (',int2str(no image loop),').JPG' ));
a2=enhansment(a);
feature=feature fourier (a2);
t=t+1;
feature(t,:)=feature;
tt=zeros(no folders,no images);
tt(no folder,:)=1;
end
target=[target tt];
end
input=feature';
net = patternnet([25 25],'trainrp');
net = train(net,input,target);
outputs = net(input);
 plotconfusion(target,outputs)
```

Second approach

```
% --- Executes on button press in classification_F.
function classification _F_Callback(hObject, eventdata, handles)
% hObject    handle to defect_or_free_F (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)
close all
clear
clc
% number folders
end_folder=input('number folders = ');
number_folder=end_folder;
tt=0;
targets=[];
for no folder=1:end folder
% number of images
   No image = input(strcat('number image folder ',int2str(no folder) ,'='));
for no image loop = 1:no_image
         % read image
im=imread(strcat(image,int2str(no_folder),'\1(',int2str(no image loop),').JPG'));
% enhansment image
[im]=enhansment(im);
% feature extraction
Feature=feature fourier(im);
tt=tt+1;
inputs(:,tt)=feature;
t=zeros(number folder,no image);
t(no folder,:)=1;
end
targets=[targets t];
end
 save('targets_inputs.mat','targets','inputs');
```

Matlab code for classification using Statistical analysis and Fourier features:

Frist approach

```
clear
clc
t=0;
target=[];
no folders=11;
no images=10;
for no folder=1:no_folders
for no image loop =1:no_images
a=imread(strcat(image,int2str(no folder),'\1 (',int2str(no image loop),').JPG' ));
a2=enhansment(a);
feature2=feature fourier(a2);
feature1=feature statistical(a2);
t=t+1;
```

```
feature(t,:)=[feature1 feature2];
tt=zeros(no folders,no images);
tt(no folder,:)=1;
end
target=[target tt];
end
input=feature';
 net = patternnet([25 25],'trainrp');
net = train(net,input,target);
view(net)
outputs = net(input);
 plotconfusion(target,outputs)
```

Second approach

```
% --- Executes on button press in classification_S_F.
     function classification _S_F_Callback(hObject, eventdata, handles)
     % hObject    handle to defect_or_free_S_F (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)
% % % % % % % % % % % % % % % % % % % % % % % % % % % % % % % % %
     close all
clear
clc
% number folders
end_folder=input('number folders = ');
number_folder=end_folder;
tt=0;
targets=[];
for no_folder=1:end_folder
% number of images
    no_image = input(strcat('number image folder ',int2str(no_folder) ,'='));
for no_image_loop = 1:no_image
         % read image
im=imread(strcat(image,int2str(no_folder),'\1 (',int2str(no_image_loop),').JPG'));
% enhansment image
[im]=enhansment(im);
% feature extraction
Feature1=feature statistical(im);
Feature2=feature fourier(im);
tt=tt+1;
inputs(:,tt)=[ Feature1 Feature2];
t=zeros(number_folder,no_image);
t(no_folder,:)=1;
end
targets=[targets t];
end
 save('targets_inputs.mat','targets','inputs');
```

Matlab code for locations of Fourier spectrum peaks:

```
   close all
clear
clc
im=imread(imgetfile);
% enhansment image
[im]=enhansment(im);
J=abs(fftshift(fft2(im)));
[x,y]=size(J);
J((x/2),(y/2))=0;
 A=J(343:373 , 515);
B=J(343 , 515:545);
 A1=A';
B1= B;
j=1;
    for i=1:31
if   0.35*A1(i)>mean (A1)
    AA(j,1)=A1(i);
    AA(j,2)=i;
end
    end
    [x,y]=size(AA);
   for i=2:x
 if AA(i,2)==AA(i-1,2)+1
     n=AA(i,1);
     m=AA(i-1,1);
    if n>m
       AA(i-1,:)=0;
    else
      AA(i,:)=0;
    end
 end
   end
   j=1;
    for i=1:31
if   0.35*B1(i)>mean(B1)
    BB(j,1)=B1(i);
    BB(j,2)=i;
end
    end
    [x,y]=size(BB);
   for i=2:x
 if BB(i,2)==BB(i-1,2)+1
     n=BB(i,1);
     m=BB(i-1,1);
    if n>m
       BB(i-1,:)=0;
    else
      BB(i,:)=0;
    end
```

```
 end
   end
     figure; plot(A1)
figure;plot(B1)
    AA(:,2)
    BB(:,2)
```

Create neural network

```
function [net]=Neural_Network_mohy(inputs,targets)
% Solve a Pattern Recognition Problem with a Neural Network
% Script generated by NPRTOOL
% Created Fri Jun 21 15:38:32 EEST 2013
% This script assumes these variables are defined:
%   inputs - input data.
%   targets - target data.
 % Create a Pattern Recognition Network
load('targets_inputs.mat')
hiddenLayerSize = 25;
net = patternnet([hiddenLayerSize hiddenLayerSize]);
 % Choose Input and Output Pre/Post-Processing Functions
% For a list of all processing functions type: help nnprocess
net.inputs{1}.processFcns = {'removeconstantrows','mapminmax'};
net.outputs{2}.processFcns = {'removeconstantrows','mapminmax'};
  % Setup Division of Data for Training, Validation, Testing
% For a list of all data division functions type: help nndivide
net.divideFcn = 'dividerand';  % Divide data randomly
net.divideMode = 'sample';  % Divide up every sample
net.divideParam.trainRatio = 80/100;
net.divideParam.valRatio = 10/100;
net.divideParam.testRatio = 10/100;
%  trainrp RPROP backpropagation.
%    trainrp is a network training function that updates weight and bias
%    values according to the resilient backpropagation algorithm (RPROP).
% For help on training function 'trainrp' type: help trainrp
% For a list of all training functions type: help nntrain
net.trainFcn = 'trainrp';
% Choose a Performance Function
% For a list of all performance functions type: help nnperformance
net.performFcn = 'mse';  % Mean squared error
 % Choose Plot Functions
% For a list of all plot functions type: help nnplot
net.plotFcns = {'plotperform','plottrainstate','ploterrhist', ...
  'plotregression', 'plotfit'};
 % Train the Network
[net,tr] = train(net,inputs,targets);
 % Test the Network
outputs = net(inputs);
errors = gsubtract(targets,outputs);
performance = perform(net,targets,outputs);
```

```
 % Recalculate Training, Validation and Test Performance
trainTargets = targets .* tr.trainMask{1};
valTargets = targets  .* tr.valMask{1};
testTargets = targets  .* tr.testMask{1};
trainPerformance = perform(net,trainTargets,outputs);
valPerformance = perform(net,valTargets,outputs);
testPerformance = perform(net,testTargets,outputs);
 % View the Network
view(net)
 % Plots
% Uncomment these lines to enable various plots.
figure, plotperform(tr)
 saveas(gcf,'1.jpg')
figure, plottrainstate(tr)
 saveas(gcf,'2.jpg')
figure, plotconfusion(targets,outputs)
 saveas(gcf,'3.jpg')
figure, ploterrhist(errors)
 saveas(gcf,'4.jpg')
```

Test image using Statistical analysis and Fourier features:

```
% --- Executes on button press in test_S_F.
function test_S_F_Callback(hObject, eventdata, handles)
% hObject    handle to test_S_F (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)
close all
clear
clc
load('net.mat')
im=imread(imgetfile);
imshow(im)
[im]=enhansment(im);
Feature1= feature statistical(im);
Feature2=feature fourier(im);
test=[feature1 feature2];
s=sim(net,test');
[p,q]=max(s);
q
```

Test image using Statistical analysis:

```
% --- Executes on button press in test_S.
function test_S_Callback(hObject, eventdata, handles)
% hObject    handle to test_S (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)
close all
clear
```

```
clc
load('net.mat')
im=imread(imgetfile);
imshow(im)
[im]=enhansment(im);
Feature=feature statistical(im);
test=feature;
s=sim(net,test');
[p,q]=max(s);
q
```

Test image using Fourier features:

```
% --- Executes on button press in test_F.
function test_F_Callback(hObject, eventdata, handles)
% hObject    handle to test_F (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)
close all
clear
clc
load('net.mat')
im=imread(imgetfile);
imshow(im)
[im]=enhansment(im);
Feature=feature fourier(im);
test= Feature;
s=sim(net,test');
[p,q]=max(s);
q
```

Test any image

Frist approach

```
load('net.mat');
im=imread(imgetfile);
imshow(im)
[im]=enhansment(im);
feature1=feature statistical(im);
feature2=feature fourier(im);
test=[feature1 feature2];
s=sim(net,test');
[p,q]=max(s);
if q==1
   display ('kont')
elseif q==2
   display('float warp')
   elseif q==3
   display('light beat')
```

```
    elseif q==4
    display('heavy beat')
    elseif q==5
    display('missing picks')
    elseif q==6
    display('double end')
    elseif q==7
    display('hole')
    elseif q==8
    display('stain')
    elseif q==9
    display('double pick')
    elseif q==10
    display('free')
else
    display('big kont')
end
```

Second approach

```
clear
clc
a1=load('net 11.mat');
a2=load('net 22.mat');
a3=load('net 33.mat');
a4=load('net 41.mat');
a5=load('net 51.mat');
im=imread(imgetfile);
imshow(im)
[im]=enhansment(im);
Feature=feature statistical(im);
test=feature;
s=sim(a1.net,test');
[p,q]=max(s);
if q==2
  display('free')
else
    display('defect')
feature = feature fourier(im);
test= feature;
s=sim(a2.net,test');
[p,q]=max(s);
if q==1
 display('area')
feature1=feature statistical(im);
feature2=feature fourier(im);
test=[feature1 feature2];
s=sim(a3.net,test');
[p,q]=max(s);
 if q==1
```

```
    display('kont')
 elseif q==2
    display('hole')
 else
    display('stain')
 end
elseif q==2
   display('warp')
feature=feature statistical(im);
test=feature;
s=sim(a4.net,test');
[p,q]=max(s);
if q==1
   display('Double end')
else
   display('Float warp')
end
else
   display('weft')
feature=feature statistical(im);
test=feature;
s=sim(a5.net,test');
[p,q]=max(s);
if q==1
   display('ligth beat')
elseif q==2
   display('heavy beat')
elseif q==3
   display('missing picks')
else
   display('Double pick')
end
end
end
```

ملخص :

يقدم هذا المشروع منظومة للرؤية باستخدام الحاسب من أجل اكتشاف وتصنيف عيوب الأقمشة المنسوجة آلياً وبذلك تستبدل مرحلة فحص الأقمشة التقليدية في مصانع النسيج والتي تعتمد على الفحص البصري للعامل. تقوم هذه المنظومة بتوظيف الكاميرا الرقمية لالتقاط صور الأقمشة ونقلها إلى جهاز حاسب يقوم بتحليل الصور واستخراج السمات المميزة لكل منها ثم توجيه هذه السمات على منظومة أخرى تعتمد على الذكاء الاصطناعي من أجل تصنيف هذه السمات وتحديد نوع العيب الموجود بالقماش. تستطيع المنظومة إخبار العامل ببعض المصادر المتوقعة للعيب وتوجيهه إلى إصلاحها، كما يتم تسجيل العيوب المرصودة في قاعدة بيانات خاصة لإعطاء تقرير دوري عن العيوب المتكررة بكثرة في الإنتاج لمحاولة إصلاح مصادرها ورفع جودة الأقمشة المنتجة. المنظومة المقترحة ستساهم في زيادة أرباح الشركات التي ستقوم بتطبيقها من خلال توفير تكاليف العمالة المدربة المطلوبة لعملية الفحص، توفير المساحات المستغلة لمرحلة الفحص، وزيادة سعر المنتج النهائي لكونه خالي من العيوب.

إهداء

بسم الله الرحمن الرحيم

(قل إعملوا فسيرى الله عملكم ورسوله والمؤمنون)

صدق الله العظيم

إلهي لايطيب الليل إلا بشكرك ولايطيب النهار إلى بطاعتك .. ولاتطيب اللحظات إلا بذكرك .. ولا تطيب الآخرة إلا بعفوك .. ولا تطيب الجنة إلا برؤيتك

الله جل جلاله

إلى من بلغ الرسالة وأدى الأمانة .. ونصح الأمة .. إلى نبي الرحمة ونور العالمين..

سيدنا محمد صلى الله عليه وسلم

إلى من علمونا العطاء بدون انتظار إلى من نحمل أسمائهم بكل افتخار .. نرجو من الله أن يرحمهم ويمد في عمرهم ليرو ثماراً قد حان قطافها بعد طول انتظار وستبقى كلماتهم نجوم نهتدي بها اليوم وفي الغد وإلى الأبد

(اباؤنا الأعزاء)

إلى ملاكنا في الحياة .. إلى معنى الحب وإلى معنى الحنان والتفاني .. إلى بسمة الحياة وسر الوجود

إلى من كان دعائها سر نجاحنا وحنانها بلسم جراحنا إلى أغلى الحبايب

(أمنا الحبيبة)

لابد لنا ونحن نخطو خطواتنا الأخيرة في الحياة الجامعية من وقفة نعود إلى أعوام قضيناها في رحاب

الجامعة مع أساتذتنا الكرام الذين قدموا لنا الكثير باذلين بذلك جهودا كبيرة في بناء جيل الغد

لتبعث الأمة من جديد ......

وقبل أن نمضي نقدم أسمى آيات الشكر والامتنان والتقدير والمحبة إلى الذين حملوا أقدس رسالة

في الحياة......

إلى الذين مهدوا لنا طريق العلم والمعرفة.....

الذي نقول لهم بشراك قول رسول الله صلى الله عليه وسلم:

"إن الحوت في البحر ، والطير في السماء ، ليصلون على معلم الناس الخير "

إلى من علمونا التفاؤل والمضي إلى الأمام إلى من وقفوا إلى جانبنا عندما ضللنا الطريق......

إلى جميع أساتذتنا الأفاضل......

"كن عالما .. فإن لم تستطع فكن متعلما ، فإن لم تستطع فأحب العلماء ،فإن لم تستطع فلا تبغضهم"

ونخص بالتقدير والشكر:

الدكتور: إبراهيم شادى. الدكتور: محمد الدسوقى.

وكذلك نشكر كل من ساعدنا على إتمام هذا المشروع وقدم لنا العون ومد لنا يد المساعدة وزودنا

بالمعلومات اللازمة لإتمام هذا المشروع ونخص بالذكر:

الدكتور: على صقر.

الذي كان عونا لنا في مشروعنا هذا ونورا يضيء الظلمة التي كانت تقف أحيانا في طريقنا.

إلى من زرعوا التفاؤل في دربنا وقدموا لنا المساعدات والتسهيلات والأفكار والمعلومات، ربما دون

يشعروا بدورهم بذلك فلهم منا كل الشكر.

جامعة المنصورة
كلية الهندسة
قسم هندسة الغزل والنسيج

منظومة ألية لفحص عيوب الأقمشة وتحسين جودة المنسوجات المنتجة

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(٢٠١٣)