UNSUPERVISED FABRIC DEFECT DETECTION VIA CLUSTERING IN SPECTRAL DOMAIN

Master of Science Thesis

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This thesis titled **"Unsupervised Fabric Defect Detection via Clustering in Spectral Domain"** has been prepared and submitted by **Sahar Shakir** in partial fullfilment of the requirement in "Anadolu University Directive on Graduate Education and Examination" for the Degree of Master of Science in **Electrical and Electronics Engineering Department** has been examined and approved on 27/05/2019.

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ABSTRACT

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Sahar SHAKIR

Electrical and Electronics Engineering Program
Anadolu University, Graduate School of Sciences, May 2019

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The purpose of this dissertation is to design an automated system using machine vision techniques for inspection of faults in textile industry. Detection of defects in fabrics has a substantial importance to prevent delivering faulted products. Because of human factor drawbacks like fatigue, boredom and oversight, manual inspection falling behind expectations of the industry. There are countless automated systems in the literature, however, most of them rely on machine learning methods where defected and defect free images are fed to the system for training or the approaches have numerous parameters to be tuned. For these reasons supervised systems are difficult and discomfort to use.

In this study, Fourier Transform based unsupervised approach used to inspect a fabric. The method does not require any prior knowledge about the fabric pattern or the defect class. Proposed algorithm obtains the spectral representation of the partitioned image and measures the distance between each part and a reference representation obtained from the same inspected sample. Although the literature crowded with automated inspection systems, a suitable dataset for textile fabric could not be found. Existent databases either not freely available or has lack of defect classes. Therefore, a dataset contains 26 defect class plus a clean class collected. The database called *Eskisehir Technical University Textile Defect Dataset (ESTD)* and consist of 2969 samples of ten diverse type of fabric.

Keywords: Fabric Defect Detection, Textile Quality Control, Fourier Transform, Machine Vision.

ÖZET

Kumaşlarda Dokuma Hatası Tespiti icin Spektral
Alanda Kümeleme Tabanli Gürbüz Bir Yöntem

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Bu tezin amacı, makine görmesi yöntemleri kullanılarak, tekstil endüstrisi için hata tespit sistemi tasarlamaktadır. Kumaştaki hataları bulmak, kusurlu ürün teslim etmemek adına oldukça önemlidir. İnsan faktörünün yorgunluk, bıkkınlık ve dikkatsizlik gibi dezavantajları yüzünden, manuel denetim endüstrinin beklentilerini karşılayamamaktadır. Literatürde çok sayıda otomatik sistemler mevcuttur ancak bunların büyük kısmı eğitmenli makine öğrenmesi yöntemlerini baz almaktadır, bu metodlar yalnış ve doğru imgeleri alarak sistemi eğitmektedir ya da ayarlanması gereken çok sayıda parametreleri bulunmaktadır. Bu nedenlerden dolayı eğitmenli sistemlerin kullanımı güç ve rahatsızlık vericidir.

Bu çalışmada Fourier dönüşümüne dayalı denetmensiz yaklaşım sunulm-uştur. Yöntem kumaş deseni ya da hata sınıfı ile ilgili hiç bir ön bilgiye ihtiyaç duymamaktadır. Önerilen yöntemde bölümlenmiş imgenin frekans uzayındaki spektral temsili elde edilmiştir. Sonrasında her bir parça ile denetlenen aynı imgeden elde edilen referans imgesi arasındaki mesafe ölçülm-
üştür. Literatürde bulunan veri kümeleri ya az sayıda hata ve kumaş sınıfı içermektedir; ya da kullanım için ücret ödenmesi gerekmektedir. Bu sebeple tez çalışması kapsamında 10 farklı kumaş türünden 26 adet hata sınıfı içeren bir veri kümesi hazırlanarak bu konuda çalışan araştırmacıların kullanımına sunulması planlanmıştır.

Anahtar Sözcükler: Kumaşta Hata Tespiti, Tekstil Kalite Kontrol, Fourier Dönüşmü, Makine Görmesi.

31/05/2019

STATEMENT OF COMPLIANCE WITH ETHICAL PRINCIPLES AND RULES

I hereby truthfully declare that this thesis is an original work prepared by me; that I have behaved in accordance with the scientific ethical principles and rules throughout the stages of preparation, data collection, analysis and presentation of my work; that I have cited the sources of all the data and information that could be obtained within the scope of this study, and included these sources in the references section; and that this study has been scanned for plagiarism with "scientific plagiarism detection program" used by Anadolu University, and that "it does not have any plagiarism" whatsoever. I also declare that, if a case contrary to my declaration is detected in my work at any time, I hereby express my consent to all the ethical and legal consequences that are involved.

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ABBREVIATIONS

FT	Fourier Transform
IFT	Inverse Fourier Transform
FFT	Fast Fourier Transform
DFT	Discrete Fourier Transform

1. INTRODUCTION

In this chapter, motivation to design and use an automated visual inspection system for fabric defect detection will be discussed. Afterwards, the objective and outline of the study will be presented.

1.1 Motivation

Textile manufacturing is a very large and competitive industry. Fabrics are main raw material of this industry with specific structure that any irregularity in structure refereed as defects. Fabric defects affect the product quality and hence the price in this field. Textile inspection systems are designed to detect faults and classify the fabric quality according to that.

Fabrics can be classified into several categories based on the inspection system used (see fabric inspection systems illustrated by Goyal [16]). In aforementioned systems, inspected fabric classified based on amount or severe of the defects or both in one fabric web. Detection and Recognition of textile defects can be very difficult task due to the 70 different types of fabric faults, including very common ones such as hole, dye spot, miss pick, double pick and thin end [14]. It has been stated that the price of fabrics is reduced by 45% - 65% due to the presence of one or more defects [2].

Until recently, textile fabric quality control was carried out manually by trained human supervisors for this purpose. Along with the disadvantages like being a very slow process, human-based visual inspection is also limited by the factors like tiredness, boredom and distraction. Detection rate of defects in fabrics using human-based manual systems is 60-75% compared to automated visual inspection systems with 90% detection rate [14]. Despite all the facts above, human-based visual inspection is still in use in the industry. Manual systems consist of human experts inspect a roll of moving fabric on a table with a lighting system behind it (as seen in Figure 1.1). As a result, there is a high demand on alternative systems for quality control without the disadvantages of human based systems. Automated visual inspection attracts attention to be an alternative for human-based inspection systems with considerably advantages.

Visual inspection process can be classified into two classes in the following [2, 17], each of which has its own pros and cons explained briefly:

(a) *© Christopher Payne/Bonni Benrubi Gallery.* **(b)** *© Karl Menzel Maschinenfabrik GmbH & Co DCT.*

Figure 1.1: *Manual inspection scenes with experts working on fabric winding in rewinder machines.*

- Online inspection.
- Offline inspection.

Online (or process) inspection is performed when quality control step is carried out with production section, which means that quality control machines or inspectors directly work on the output of weaving machines. This type of inspection will allow the inspector to not only detect defects, but also control the weaving process too. In process inspection the supervisor will have the ability to detect patterned faults which may caused by faulted machines and prevent more defected product. If production is intercepted to prevent manufacturing defected fabrics or to remove or mark faulted regions; it will slow down the entire production process and causes loss of money and time. In addition, online inspection approaches should be fast enough to match the speed of production line.

Offline (or product) inspection is performed when quality control step carried out after a production section. This means that entire web of fabric manufactured and moved to different section for inspection. Advantage of product inspection is to keep human supervisors far away from weaving environment that could be very harmful for human body. Although when using automated inspection methods no human experts needed, but an observer for monitoring the host computers will possibly needed. Defect detection approaches could be more flexible in terms of computation time when inspection processed in a different section since there will be no production speed to keep up. Only handicap of product inspection is that there will be no control over the manufacture section hence machine based damages can't be avoid or reduced.

Eventually, the type of inspection used depends on the usage of the fabric and the preference of the manufacturer. As informed from fabric manufactures, recently most factories prefers offline inspection because enormous time consumed while interpreting the weaving process each time a defect occurs. Another aspect is that product acquired from weaving will be sent for dyeing, in which dye related faults may happen and/or some other faults become more visible. In cases like this, offline inspection is obligatory.

A typical Automated visual system have a fixed components (like displayed in Figure 1.2). The inspection framework needs a base to set and roll the web over it. The illumination controlled by a lighting system based on the amount of the illumination in inspection environment to minimize noise. Simultaneous cameras used to capture images and sent them to frame grabber for collecting visual data. Finally host computer containing defect detection algorithm, analyzes the images and notify the user or mark the faulted parts.

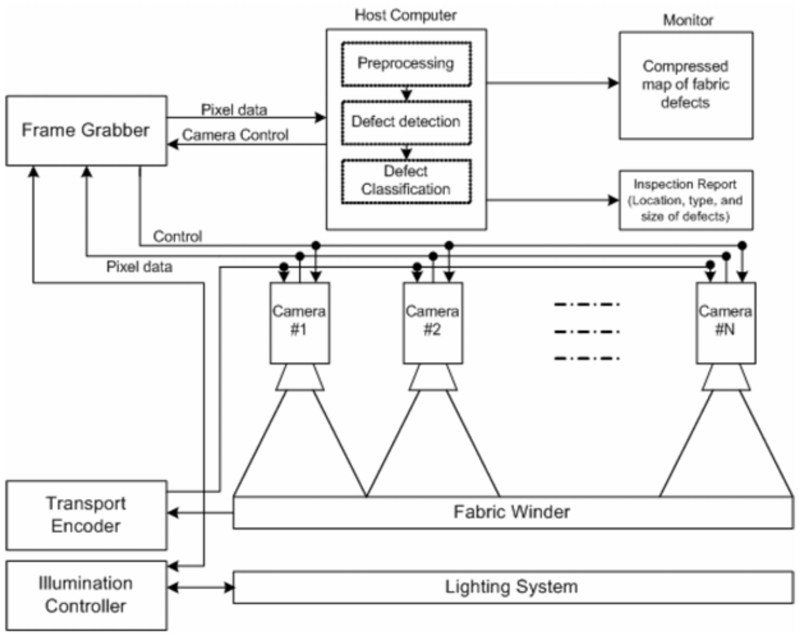


Figure 1.2: *Architecture of a typical automated visual inspection system for textile web [2].*

1.2 Main Research Objectives

Even though there is a crowded literature on the studies targeting machine-vision based textile fabric inspection, difficulty of the problem and diversity of the fabrics and defect types becloud this critical technology to become prevalent and be utilized by majority of the industry. The majority of the methods in the literature require a defect free patch to obtain a valid representation to compare with the input images. However, this hinders the applicability and ease of use of the methods due to the diverse range of fabrics and defect types.

In this study, a simple yet quite accurate method proposed for unsupervised defected fabric detection that works without the need of a training phase. Instead of learning the structure of an input defect-free fabric, the method estimates an frequency domain representation for the fabric by averaging Fourier spectrum of local patches in a fabric. In this manner, a stochastic approximation for the fabric's texture pattern is obtained. Then that representation compared to each of the patches -which already contributes to computation of that representation- and calculate the variance between patch pairs to see whether there is a discrepancy. Thus, proposed method not only detects defected fabrics, it also localize the defected areas.

Even though the related literature is very rich, there was difficulties on comparing proposed method in a quantitative manner during the experiments due to the lack of a comprehensive and free dataset for defect detection. For the same reason, many studies in the literature test their method on either synthetic images or a very limited set of real images. Therefore, a textile dataset called *Eskisehir Technical University Textile Defect Dataset (ESTD)* prepared. This database consist of 2969 images of ten different fabrics and 27 defect types.

1.3 Outline of Thesis

In Chapter 2, a summary of related works for defect detection and classification presented briefly. Earlier works, classified the fabric into two classes (i.e. motif based and non-motif based) and designed approaches independently for each class. Then for each fabric type, several feature extraction methods reviewed.

In Chapter 3, hybrid of spectral and statistical based method proposed for non-motif fabric inspection. Fourier Transform obtained from sliding windows and combined with statistical techniques where reviewed on details.

In Chapter 4, summary of available datasets in the literature discussed. A database consist of 10 type of fabric texture for defect detection named ESTD presented with example on each fabric and each defect class.

In Chapter 5, Empirical evaluation of the proposed method on ESTD and Dot, Box, and Star patterns dataset offered. Window size effects on detection results and localization examined. Finally, quantitative results and comparison with two state of the art methods given.

In Chapter 6, we summarize the thesis study and provide suggestions for future work.

2. RELATED WORK

The related works on fabric defects inspection explore the problem from two aspects [18]:

- Detection.
- Classification

Detection based approaches focused only on detecting the defected samples. While classification based approaches intend to find the defected sample then classify the defect found.

The classification task has a wide range of approaches in the literature. The classifier needs to be trained for every defect type with a training sample individually, so over than 70 types of defect make the classification task difficult. Some authors train the classifier considering only 2 classes, defected and defect free. Lately it can be seen that almost there is no classification based research, the main reason is the textile industry does not need the defect type as they interest if it's defected or not. As a result, our main interest will be on detection algorithms but some notable classification studies will be mentioned in seek of generalization.

According to [14], general fabric defect detection methods can be classified into six categories, i.e. spectral, statistical, model-based, learning-based, structural and hybrid. There are another category utilized for special patterns (Wallpaper Group [19]) called approaches for motif-based textiles, these algorithms designed for each paper group individually. Moreover, some approaches in general categories designed specially for only plain or twill or some specific direction lines and patterns in the texture. In this chapter some prominent example of existing methods for each six categories besides motif-based category reviewed briefly.

2.1 Approaches for Textiles without Motif

2.1.1 Spectral approaches

A textile fabric consists of two set of threads, i.e. warp and weft, which have a regular and repetitive pattern that can be best characterized in frequency domain by various transformation techniques like Fourier Transform, Wavelet Transform, Gabor filtering, etc. Any break in the regularity of warp or weft or both will lead to a change in various strengths in Fourier representation of the fabric image. Therefore, Fourier analysis have been used widely in the fabric defect detection. One of the first attempts to using Fourier Transform in inspection and classification done by Chan and Pang [3]. They propose to utilize a partial region of frequency spectrum around the central peak diagrams (illustrated in Figure 2.1) to detect four classes of defects, i.e. double yarn, missing yarn, webs or broken fabric and yarn densities variation. Seven features are extracted from the central spatial frequencies and compared with the features extracted from defect free fabric. Although this method is one of the first examples of frequency domain methods, it has several drawbacks such as limitation of defect types, missing small defects and lack of defect localization.

Another approach employed for textile defect detection is similar to image restoration algorithms which modify Fourier representation of fabric image and take the inverse Transform to eliminate the texture and reserve the faults only. In [4] 2D Fourier Transform is applied to obtain frequency response of periodic line patterns of the texture and removes them before taking the inverse. Since regular line textures leads to high energy frequency component in the spectral domain, it is easily detectable as seen in Figure 2.2(b). As a result of removing the repetitive patterns of texture in Fourier domain using 1D Hough Transform and then inverse transforming to the spatial domain, the defect only will be kept in the restored image, while the defect free regions will have a gray level (shown in Figure 2.2(c), 2.2(d) and 2.2(e), respectively). Finally a simple threshold operation discriminate the two regions (Figure 2.2(f)).

The same concept used by Tsai and Huang [20] for statistical textures that have randomly distributed patterns. Statistical textures differ from structural that their frequency component form the shape of circle around the center. The approach determines adequate radius in the frequency domain of the surface image that have the texture information in low frequency component. Setting outside of the circle selected and the center of frequency component to zero and back Transform to spatial domain to maintain only the defect. In the resultant image the texture region will have gray level while defects will have darker color approximately and the rest is threshold operation. The algorithm in [4] developed for structural directional textures only while the algorithm in [20] developed for statistical textures hence both methods can not be generalized as a quality control method for textile fabrics.

There are methods using Wavelet Transform to reconstruct smoothed image which contains only the defect and wipe the texture. Tsai and Hsiao [21] implemented Wavelet Transform in different decomposition levels to acquire two-level

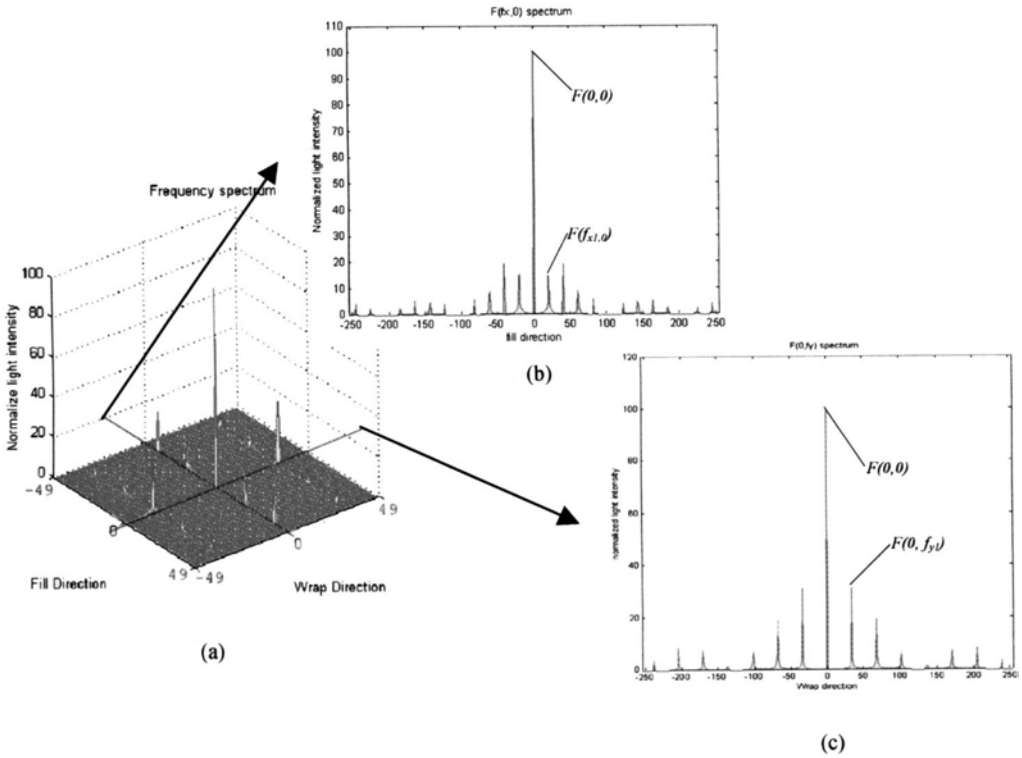


Figure 2.1: *Frequency spectrum [3] (a) Portion of faultless fabric frequency magnitude spectrum. (b) Fill direction frequency spectrum. (c) Wrap direction frequency spectrum.*

image representation, from wavelet sub-images and bases obtained they select the ones that output an image free of texture in the reconstruction procedure. Although extensive tests performed on structural and statistical texture surface like textile fabric, natural woods, leather and sandpaper, no dataset used for quantitative evaluation.

Tong et al. [22] used two optimized Gabor filters instead of Gabor filter bank to segment defects from pattern. They gained the perfect Gabor filter parameters by using composite differential evolution (CoDE) to obtain features able to extract the defected parts from the fabric background. After future extracted the model supported by fusion and thresholding operations for detection. Filters optimization as offline and defect detection as online modules intended to reduce the computational cost of the process with higher detection rate. The reliability of the method tested on two databases, one their own dataset of images of fabrics taken under sunlight which is not published, the other one is images of fabric scanned from fabric defects handbook [23]. Li et al. [5], proposed an approach focused on detecting abnormalities in direction of the patterned fabrics. For this purpose they designed a descriptor based on Gabor, histogram of orientated gradients (GHOG) and low-rank

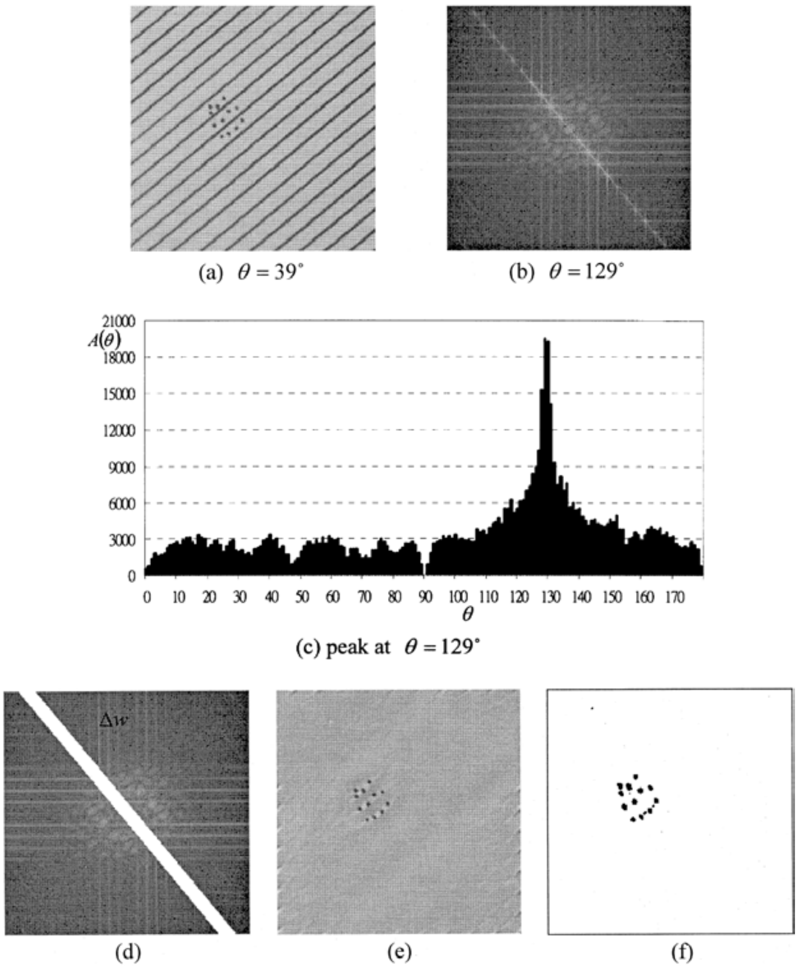


Figure 2.2: *A line-structural texture example from [4] with dot-spot defect: (a) The original image; (b) The Fourier domain image; (c) The slope-angle histogram in the Hough space; (d) The notch that contains high-energy frequency components; (e) The restored image; (f) The detected dot spots displayed as a binary image.*

decomposition that can sense the irregular directions (see construction process of GHOG descriptor in Figure 2.3). They used Gabor and HOG as feature extractor and low-rank decomposition model which solved by using an alternative direction method of multipliers (ADMM) optimization method to differentiate the defect from the background in the feature space. Experiments conducted on Dot, Box, and Star patterns database [1] and compared with other Gabor filter based works.

2.1.2 Statistical approaches

Statistical based algorithms analyzes the fabric texture image by mean of spatial distribution of the gray level i.e. first-order statistics, cross correlation, edge detection, morphological operations, co-occurrence matrix, Eigen filters, etc. Some of the

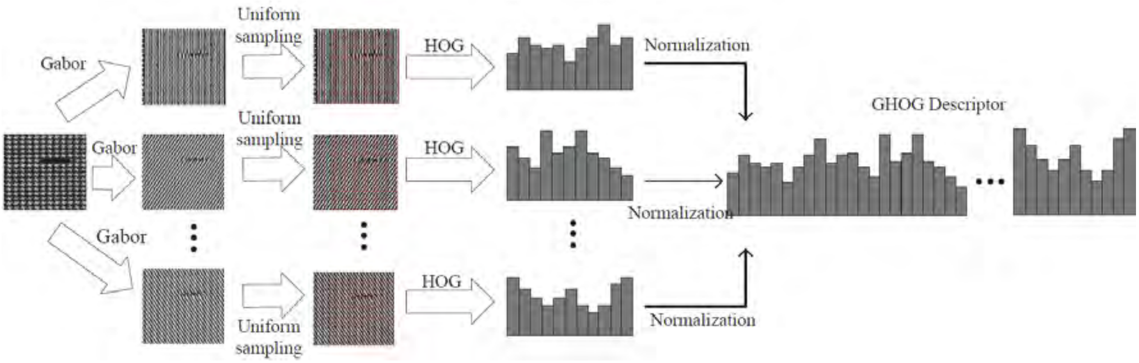


Figure 2.3: *Construction process of the proposed GHOG descriptor [5].*

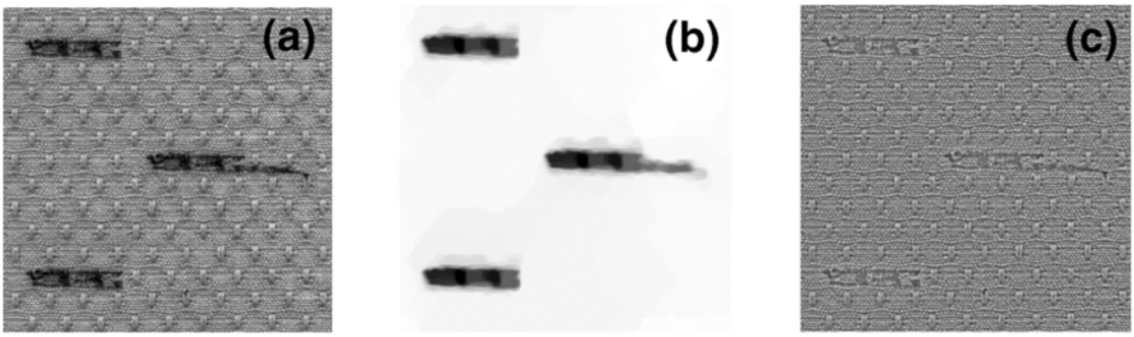


Figure 2.4: *Visualization of ID method [6]. (a) Dot-patterned fabric with "Thin Bar" defect. (b) Cartoon (i.e., defective objects). (c) Texture (i.e, patterned fabric).*

statistical based approaches mentioned now.

Image decomposition method [6] represents each component of defected image separately as cartoon (contains the defects) and texture (contains the pattern) as shown in Figure 2.4. The system optimized by seeking for the highest correlation between a reference defect free sample and the texture of the inspected image. Although the optimization process requires only single defect free sample, it needs a sample from different defect types to find the parameters and that will limit the methods usability.

Local binary pattern (LBP) extracts feature based on the spatial arrangement of the pixels (Figure 2.5 illustrates the procedure of extracting LBP features). Maenpaa et al. [7] used LBP features with self-organizing maps (SOM) to inspect several kind of surfaces including paper and images from Outex database. The first attempt to detect fabric defects using LBP achieved by Tajeripour et al. and Fekri-Ershad et al. [24, 25] in which adaptive one dimensional LBP introduced. The algorithm consist of two step, in the training a defect free image used to calculate a threshold by implementing the adaptive LBP on the entire image then partition the image to

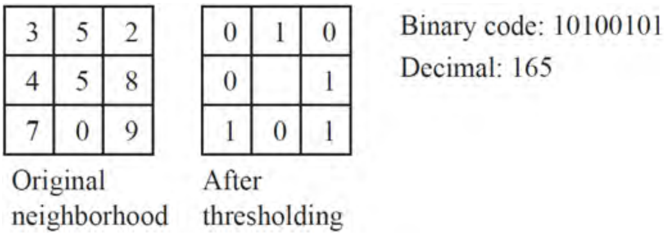


Figure 2.5: *Calculating the non-interpolated $LBP_{8,1}$ [7]. The binary code is read counter-clockwise starting at "8".*

implement adaptive LBP on each part and by comparing the feature vectors from each window with the overall feature vector they can specify the threshold. in the testing stage, inspected image divided into windows and based on threshold the resultant LBP feature vector of each window will be marked as defected or defect free. Performance of the method evaluated on patterned [1] and unpatterned fabric databases.

Mamic and Bennamoun [26] presented an approach in which features are extracted using Karhunen-Loève (KL) Transform and defects are detected by Neyman-Pearson detector. Eigenvalues of the KL Transform are extracted from the moving window in the input image and used to discriminate the faults. The defect free region of the fabric is assumed to have an eigenvalue distribution in the shape of a multivariate Gaussian and any distribution differ from that considered as defect. Although stated that Neyman-Pearson detector accomplished higher detection rates yet not enough empirical evaluation presented. In a study by Monadjemi et al. [27], Eigen filters used for reconstructing random texture images. They reconstructed the image twice, first by using it's own subset of Eigen filter, second by using a subset of a reference Eigen filter bank. Finally, reconstruction error between two resultant images is computed to detect faults.

By an attempt of simulating biological visual perception mechanism of human, Li et al. [28] presented an inspection model based on multi-channel feature extraction and joint low-rank decomposition. They utilized second-order gradient information to extract features from texture. based on low-rank decomposition, Saliency map used to obtain background matrices denoted as low-rank and the defect matrices denoted as sparse matrices. The last step is a threshold operation on sparse matrix to segment the defect.

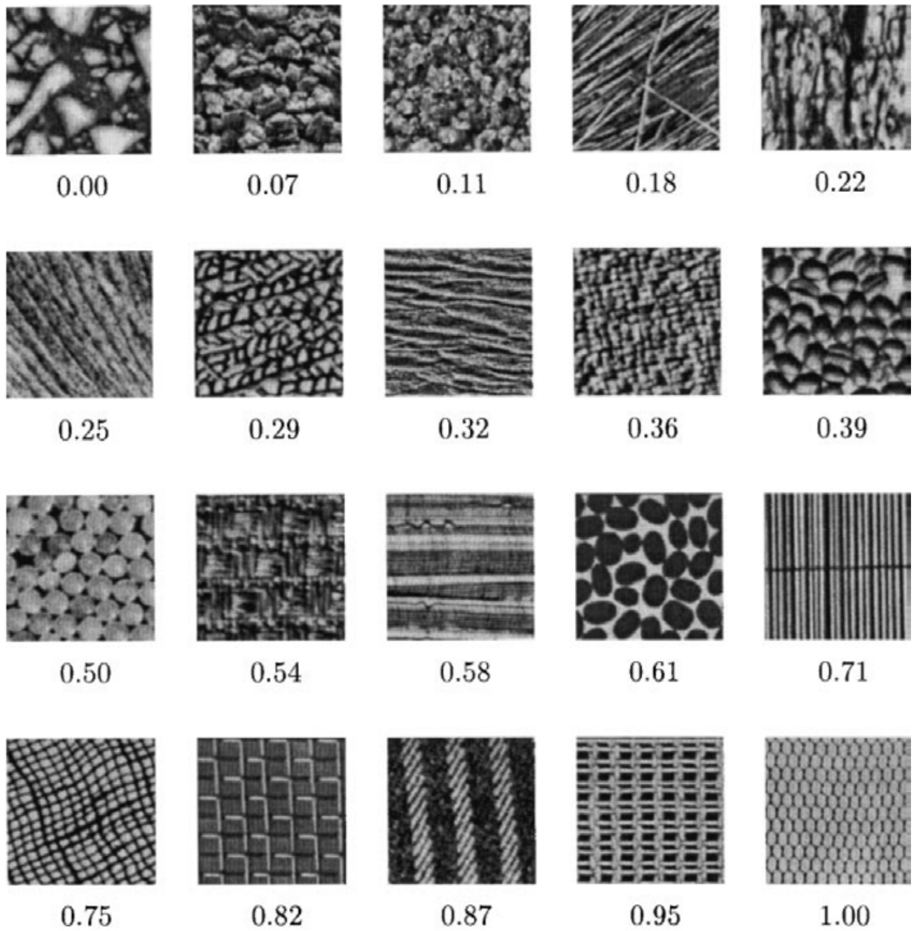


Figure 2.6: *Pattern and their maximal regularity values [8].*

2.1.3 Structural approaches

Structural models regard the texture as a combination of primal texture. Based on some replacement rules, the texture repeated primitive. An interesting work about pattern regularity is presented by Chetverikov [8]. The research aimed to obtain affine invariant feature vector and close to human perception about regularity of the texture. A feature vector extracted from the interaction map of a texture image. After computing the directional regularity, four-component regularity feature vector defined. Among the features maximal regularity feature chosen for having more satisfying results. Example of maximal regularity on different texture shown in Figure 2.6 we can see the higher degree regular textures tends to have higher regularity values which matches human perception of regularity. Also different interaction map definitions are discussed in details. Regularity measure used in three application, first, in affine invariant texture classification, second, in detecting of regular structures in aerial images, finally, inspecting texture images for structural abnormalities.

Chetverikov and Hanbury in [29] intended to isolate the structural defects in all kind of regular textures. Two kind of approaches presented. In the first, features extracted using regularity algorithm introduced earlier in [8]. Then, outlier detection method is proposed for detecting the features fall apart from the center of the cluster which obtained earlier by defect free reference image. In the second, an orientation based approach applied to find dominant orientation in textures. Both methods tested on TILDA [30] and Brodatz [31].

Susan and Sharma [32] used non-extensive entropy with Gaussian gain to measure the regularity of the texture. As mentioned by authors the regularity of the texture and highly repeated pattern leads to lower entropy values. Therefore, entropy could be a good identifier for regular textures. The entropy values obtained in each sliding window compared with reference one determined from overall patches. Window size for measuring the non-extensive entropy with Gaussian gain for each texture chosen automatically. For this purpose window size from 3 to 64 tested and the size with minimum value of entropy for the modeled entropy distribution decided as optimum window size.

2.1.4 Model-based approaches

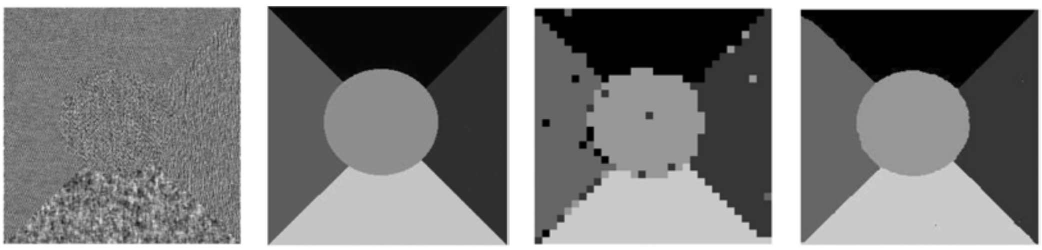
Model based methods can be categorized into three categories [14]. Covariance models, autoregressive models and the 2D models (casual, semi-casual and noncasual predictions). Due to insufficient performance, model based approaches abandoned and there was no research attempts in the last years. Most popular two models in this category are Markov Random Field (MRF) and Autoregressive (AR).

Cohen et al. [33] attempt to define the texture image by Gaussian Markov Random field (GMRF). The method first represent partitioned nondefective fabric image using GMRF then inspected partition classified into defected or defect free based on likelihood test. 2D quarter plane autoregressive model proposed by Alata and Ramananjarasoa [9] for texture image segmentation. Two stage segmentation algorithm implemented (outcome of the algorithm presented in Figure 2.7), first estimating the number of textures and the parameter related to this texture, second estimating maximum posteriori of the label field.

2.1.5 Learning-based approaches

In the latest year learning based method attracts attention more than other methods, the main reason behind this is the superior success of the neural networks in different research area. thia because neural networks began to present high in almost all the fields it One of the first attempts of neural network in fabric inspection done by Kumar et al. [34]. Principle component analysis (using single value decomposition method) utilized to reduce the dimension of the feature vector extracted for every pixel from the gray level arrangement of the neighboring pixels. Two classifiers trained (i.e. feed forward neural network and support vector machines) and compared their results. Furthermore in [35], Kumar presents another method using linear neural network with a single layer which can classify an object into two categories, defected or defect free. This method has low computation time which makes it more suitable for real time inspection.

Until now, reviewed methods all based on features extractors which designed and developed by experts. Convolutional neural networks (CNN) as a type of deep neural networks (DNN) extract their own set of features and use it to feed a neural network for learning. CNN's has proved their efficiency on analyzing visual mate-



(a) **(b)** **(c)** **(d)**

Figure 2.7: 256×256 *image containing five textures synthesized from five QP AR model with different model orders [9]. (a) Image with synthetic textures. (b) True label field. (c) Bloc segmentation after clustering algorithm. (d) Label field estimation after simulated annealing.*

rials and used in several field like object recognition, image classification, medical image analyzing and automatic inspection systems. Li et al. [36] presented a Wide-And-Compact Network (WACNet) architecture for fabric defect classification and object recognition. WACNet is CNN network using different micro architectures and optimized by multilayer perceptron. Meanwhile a method combining compressive sensing and the convolutional neural network (CS-CNN) carried out by Wei et al. [10]. The big size of the image make it very tedious task to train a CNN network with high number of images from this point CS-CNN designed (Figure 2.8). Compressive sampling theorem used to reducing the size of fabric images before train the classifier. Experimental evaluations conducted on the fabric defect images dataset (FDI 500) which contains ten type of defect classes with 50 images per each class.

Deep learning method introduced for the first time in this field by Li et al. [37]. They used defected and defect free patches of fabric samples to train Fisher criterion-based stacked denoising autoencoders (FCSDA). Inspected fabric image classified into test image to defected or defect free. The model optimized by obtaining a residual image between the reconstructed matrix and defective sample, by simple shareholding process the defect confirmed.

Eventually, Learning based method could have high detection rates but at the expense of computational power. Besides many obstacles like lack of a dataset, with

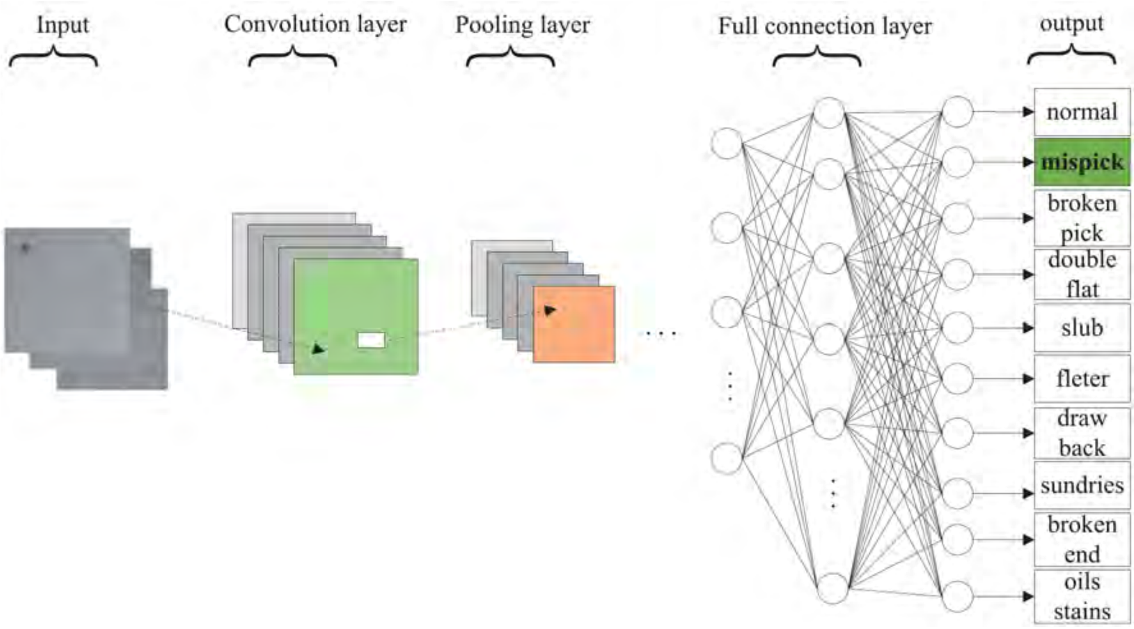


Figure 2.8: *The structure of convolutional neural network (CNN). The input image uses the fabric defect "mispick" as an example [10].*

high number of fabric types and defect classes. Slow computational time, due to training time and huge architectures. Therefore, learning based methods for fabric inspection need further investigation.

2.1.6 Hybrid approaches

There are methods combines two or more approaches together to assist each other or overcome disadvantage of one of the methods. As seen in the literature hybrid approaches tends to have higher success rates and used more frequently in the recent years. Some particular approaches demonstrate need to merge or have support more than others, like spectral methods that act like a good feature extractors but unable to separate defected features from defect free.

Ngan et al. [11] introduced three wavelet based methods for repetitive patterned textures. The first method is direct thresholding (DT) in which Haar wavelet used to obtain fourth level vertical and horizontal details (previewed in Figure 2.9) and after thresholdig and denoising steps Or-operation executed with typical features extracted the same way from three defect free samples. The second method first presented in [38] called golden image subtraction (GIS) in which golden image

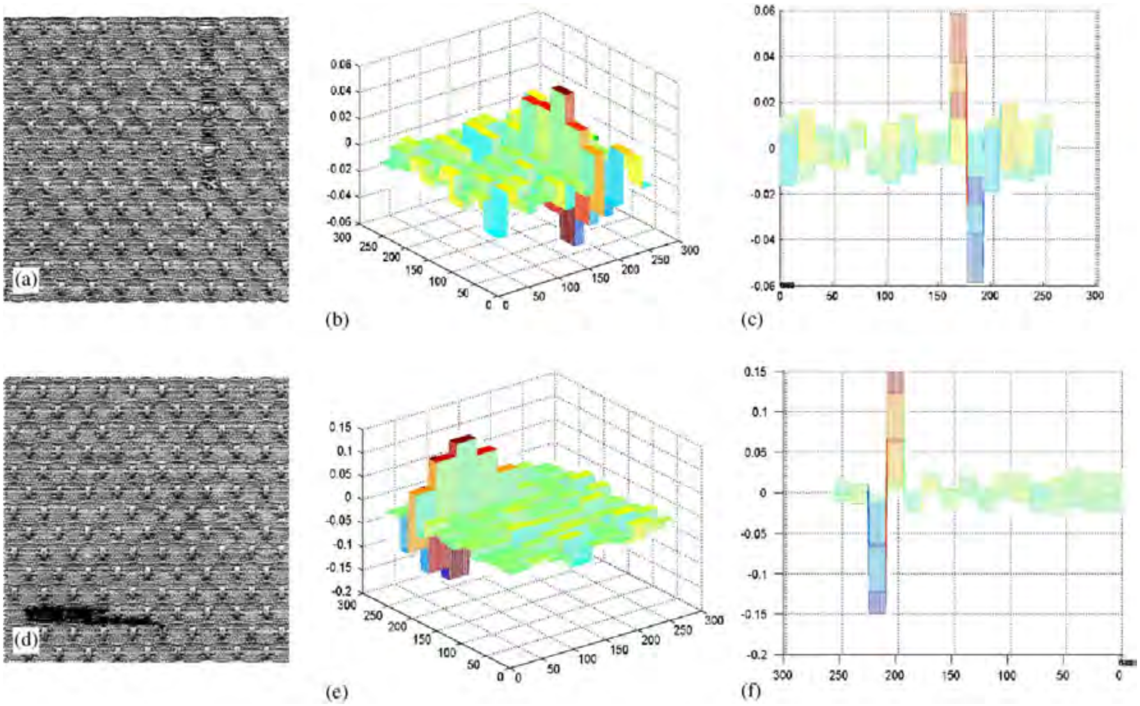


Figure 2.9: *Histogram equalized defective patterned image with (a) Broken yarn, (d) Oil stain, (b), (e) Diagonal view and (c), (f) Longitudinal view of fourth level vertical and horizontal detail after Haar wavelet decomposition respectively [11].*

obtained and subtracted from the tested image, the energy of the eventual matrix measured and after the noise removed thresholding and smoothing applied. The third method is wavelet preprocessed golden image subtraction. This method intended to remove the noise from the inspected images by performing first level Haar wavelet on histogram equalized image then obtaining golden image and applying the procedure in the second method. Experimental results shows that WGIS had the best detection rates among others. All three algorithms tested on Dot-pattern from Dot, Box and Star patterns database [1], which limited with 60 samples and six defect class. Since the algorithms compared only with each other, methods reliability on larger dataset is not clear. A research by Han and Shi [39] emphasizes on the part of selection a proper decomposition level on wavelet Transform by analyzing the co-occurrence matrices of the sub-images. The chosen decomposition level must removes the texture on the background of the image to maintain only the defects.

Six wavelet Transform based defect classification approaches presented by Yang et al. in [40]. The only joint thing between six methods is the feature extractor

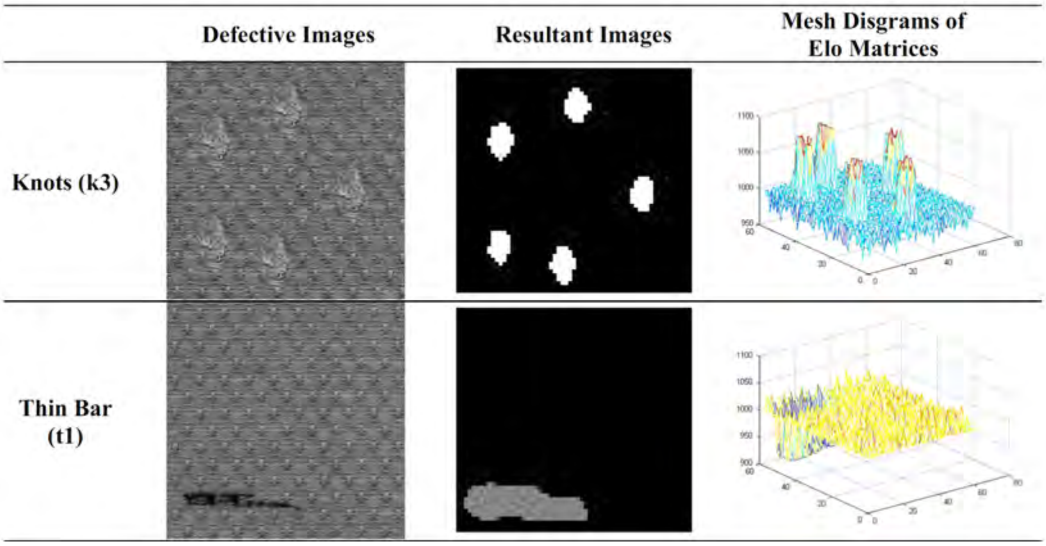


Figure 2.10: *(1st column) Defective sample names; (2nd column) Defective images; (3rd column) Detection results; (4th column) Mesh diagrams of the Elo matrices [12].*

method wavelet Transform (five of them standard wavelet and the last is adaptive wavelet). Several Training methods (maximum likelihood and minimum-squared-error) used to train neural network and Euclidean classifier and in different combination to find the best among them. Algorithm tested on 466 defected samples contain eight class of defects and best method confirmed to be discriminative feature extraction (DFE) training approach using adaptive wavelet. While Rohrmus [41] utilized statistical features extracted from local integration of the divided image and used to feed forward neural network for classification task.

Malek et al. [42] optimized spectral approach (Fourier Transform) by emerging with statistical approach (cross-correlation). Seven central frequency features of Chan et al. [3] used but instead of extracting them from the entire image, sliding window technique used to partition the image and computing FFT on each part. The second step is calculating the average feature correlation coefficient from a reference defect free image to be compared with the features extracted the same way from the inspected images. The last contribution of the work is level selection filter, which could be considered a technique to check the detected defects again to ensure their existence and reducing fault detection error. The algorithm tested on synthetic images and on real images and both images data acquired by the researchers.

Recently Tsang et al. [12] presented a method to match between partitions of the inspected image using Elo rating method [43]. It is a system that enable us to predict the final result of the match using the scores of multiple players. Light defect

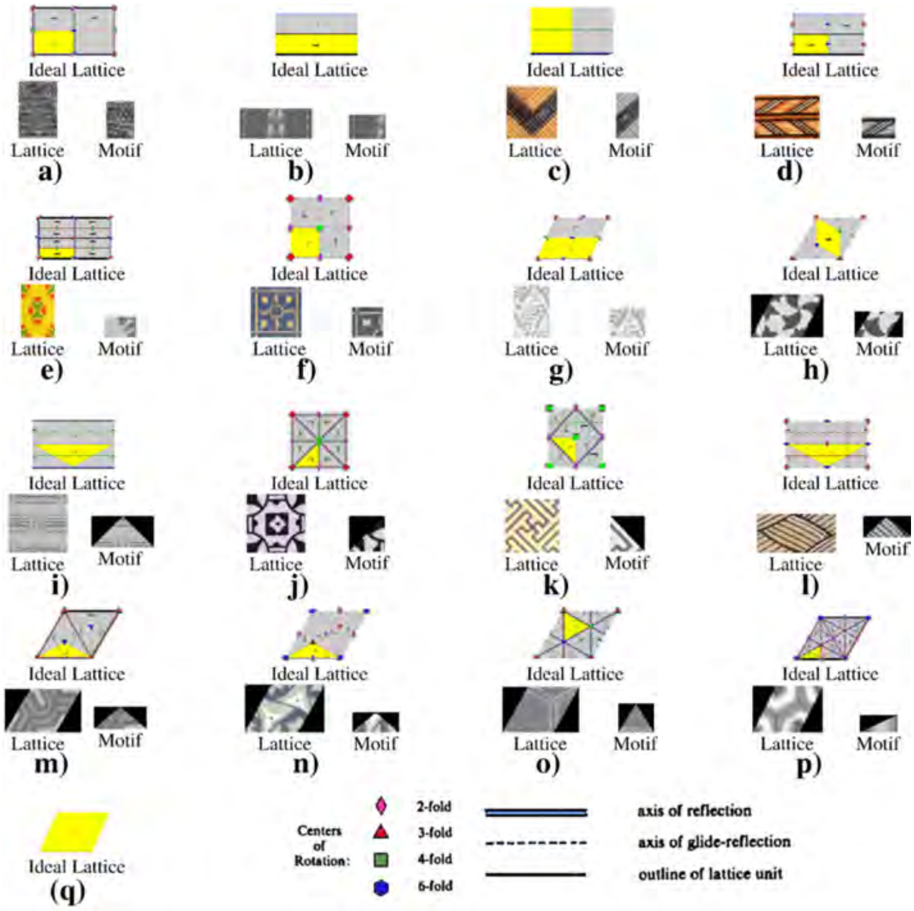


Figure 2.11: *Ideal lattice [13], lattices and motifs for 17 Wallpaper Groups [14]:(a) pmm, (b) pm, (c) pg, (d) pmg, (e) cmm, (f) p4, (g) p2, (h) p3, (i) cm, (j) p4m, (k) p4g, (I) pgg, (m) p31m, (n) p6, (o) p3m1, (p) p6m and (q) p1.*

will be strong player predicted to win, dark defects will be weak player predicted to lose while defect-free partition will be average player predicted tied results. After matching all partitions, the score of each partition updated and checked if it's in the score boundary obtained in the training stage. After the match the resultant image thresholded, if the defect is light it will be grey color, if it is strong it will be white and if it's defect free it will look black as shown in Figure 2.10 Although it obtains high detection rate on Dot, Box and Star patterns dataset, the method has five parameters to be selected manually and it is slow for that reason can't be used in online inspection.

2.2 Approaches for Textiles with Motif

Wallpaper Group stated that any two dimensional repetitive pattern based on symmetry could be classified only into one of seventeen groups (see Figure 2.11 for all the categories). The seventeen possible classes theory has been studied and proved

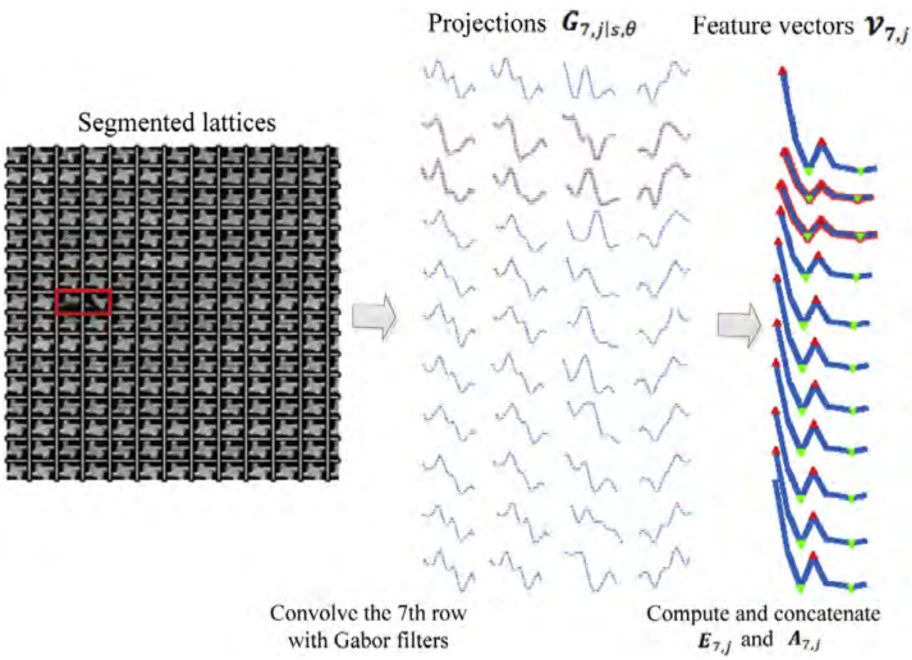


Figure 2.12: *Illustration for feature vectors [15].*

by several researchers [13]. Each pattern consist of combination of various number of lattice and in different directions (symmetries). Motif based methods extract the smallest components of a pattern and model the texture by finding their spatial arrangements in a lattice structure.

Ngan et al. [44, 45] proposed a method to extract motifs which are constituents of the lattice. In the beginning by using Liu et al. method [19] the algorithm extracts an ideal lattice then a motif as reference image, and after irregular motif shapes transformation completed the decision boundaries are obtained. In the inspection step, by moving reference motif over the inspected motif it obtains the energy and variance of the energy in every move to construct energy-variance map. Finally, energy and variance are compared with boundaries obtained from the training step. Extensive empirical evaluation [46] carried out on 16 out of 17 Wallpaper category yet it is not clear which database they used and what is the properties of the images in that database besides they didn't compared their algorithm with any other in the literature.

Jia et al. [15] segments lattice from image by utilizing morphological component analysis (MCA). Each row of the segmented lattice convolved with Gabor filters to obtain feature vectors as illustrated in Figure 2.12.

The final step is measuring the distance between the feature vectors of inspected image and a feature vector of ideal lattice learned during the segmentation process. Proposed lattice segmentation assisted by Gabor filters method (LSG) achieves high detection rates on textile fabrics which comprise of geometrical patterns in a lattice arrangement. However, it requires patterns to have high contrast between the patterns and the background in order to extract the lattice structure correctly.

Generally, motif based methods cannot perform efficiently for other fabrics which does not have a latticed pattern. As a result, considering the diversity of fabric patterns and colors, these methods can only be applied to a narrow subset of fabrics.

3. PROPOSED METHOD

3.1 Introduction to Fourier Transform

Fourier Transform (FT) theory states that any periodic function can be decomposed to frequency components. FT represents a signal or function of time as a sum of sinusoidal functions with different frequencies and amplitudes. Fourier analysis used in wide field of application, like signal processing, diffraction and interference of light, differential equations and many applications related with engineering and mathematics.

FT has some properties that could be very useful in repeated textured materials. Fourier spectrum is invariant to translation and thus removes necessity of strict alignment of fabrics before processing. Another property of FT is orientation variant which means that a horizontal line structure in the spatial domain appear a vertical line (orthogonal) in the spatial domain [4] as seen in fabric samples and their magnitude of FT representation in Figure 3.1.

Because of aforementioned advantages and others like noise immunity which remove the necessity of considerable preprocessing steps and boosting periodic features Fourier analysis used widely and effectively in texture analysis.

Mathematical expression of two dimensional FT given in equation 3.1. Where $f(x,y)$ is two dimensional signal (gray level image) and $F(u,v)$ is two dimensional frequency domain representation of that signal.

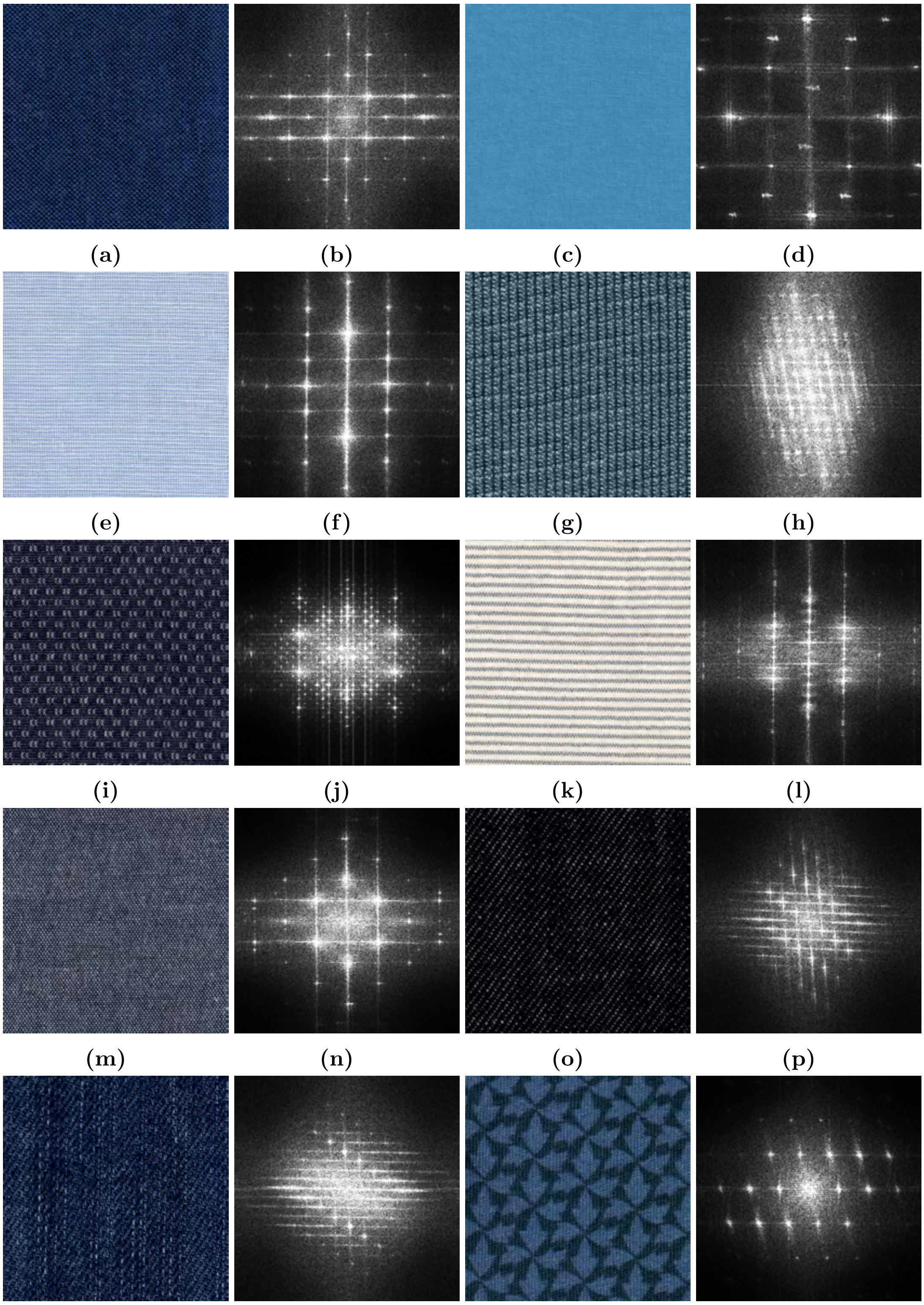
$$F(u,v) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x,y) e^{-j2\pi(ux + vy)} dx \; dy \tag{3.1}$$

Where (x,y) and (u,v) coordinates in spatial domain and spectral domain, respectively.

An important property of FT is the ability to restore spatial domain signal using inverse Fourier Transform, this property used in various works in different research area. IFT given by:

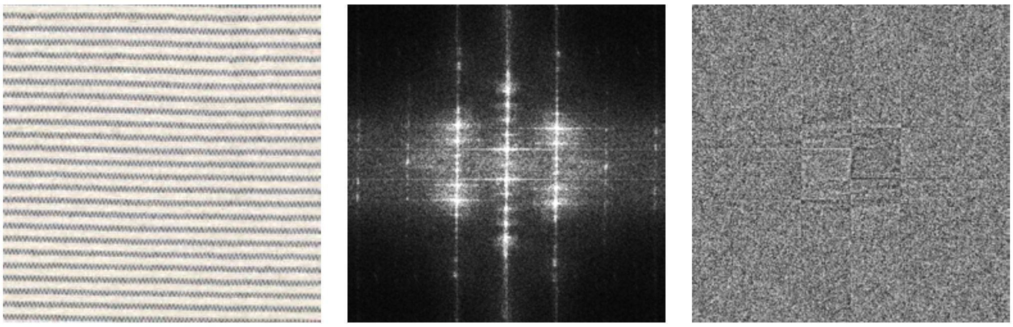
$$f(x,y) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} F(u,v) e^{j2\pi(ux + vy)} du \; dv \tag{3.2}$$

In digital communication Discrete version of FT called DFT, which utilized for obtaining frequency domain image. DFT is equivalent to the continuous FT, it only



(a) (b) (c) (d)
(e) (f) (g) (h)
(i) (j) (k) (l)
(m) (n) (o) (p)
(q) (r) (s) (t)

Figure 3.1: *Fourier representation (magnitude) of* 512×512 *image samples from ESTD database. For better visualization of FT images, zero frequency components shifted to center of the images and intensity values are scaled*



(a) **(b)** **(c)**

Figure 3.2: *(a) Sample fabric image from proposed database. (b) Fourier spectrum magnitude of sample image given in (a). (c) Fourier spectrum phase of sample image given in (a).*

converts a finite set of equally spaced intervals (pixels) to a finite set of spectrum representation. Where $m \times n$ number of data (image width and height). The DFT and IDFT expression given in equations 3.3 and 3.4, respectively.

$$F(u,v) = \sum_{x=1}^{m}\sum_{y=1}^{n} f(x,y)e^{-j2\pi(\frac{ux}{m} + \frac{vy}{n})} \tag{3.3}$$

$$f(x,y) = \frac{1}{mn}\sum_{u=1}^{m}\sum_{v=1}^{n} F(u,v)e^{j2\pi(\frac{ux}{m} + \frac{vy}{n})} \tag{3.4}$$

Computing time of DFT is very long. For this reason DFT implemented using numerical algorithms specially fast Fourier Transform method. The computation time of two-dimensional image DFT is N^2 while using FFT, the computation time is $2N^2 \; log_2 \; N$, where $m \times n = N$. FFT used separability property of two-dimensional DFT, which allow to represent two-dimensional matrices using two one-dimensional FT's.

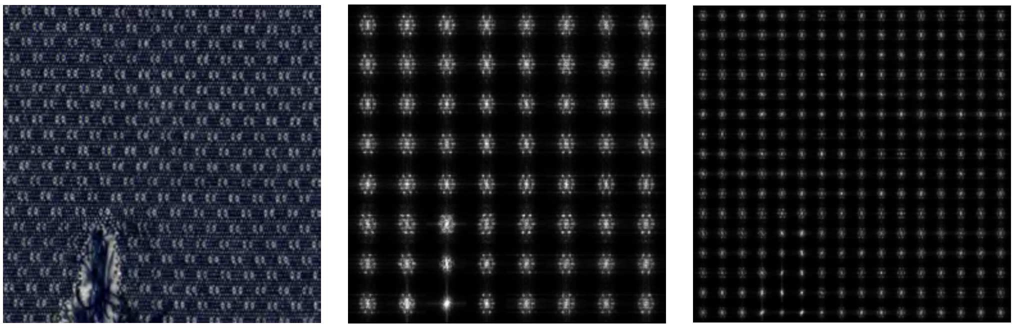
Fourier spectrum signal is a complex number consist of real $\Re(u,v)$ and imaginary $\Im(u,v)$ parts where each given below:

$$F(u,v) = \Re(u,v) + j \; \Im(u,v) \tag{3.5}$$

$$\Re(u,v) = \sum_{x=1}^{m}\sum_{y=1}^{n} f(x,y)cos[2\pi(\frac{ux}{m} + \frac{vy}{n})] \tag{3.6}$$

$$\Im(u,v) = \sum_{x=1}^{m}\sum_{y=1}^{n} f(x,y)sin[2\pi(\frac{ux}{m} + \frac{vy}{n})] \tag{3.7}$$

In textured images, most of the repetitive and uniform structure information preserved in magnitude of the FT. Therefore, frequency magnitude extracted and used



(a) (b) (c)

Figure 3.3: *(a) Defected fabric sample. (b) Magnitude of local spectra of (a) using* 64×64 *patch size. (c) Magnitude of local spectra of (a) using* 32×32 *patch size.*

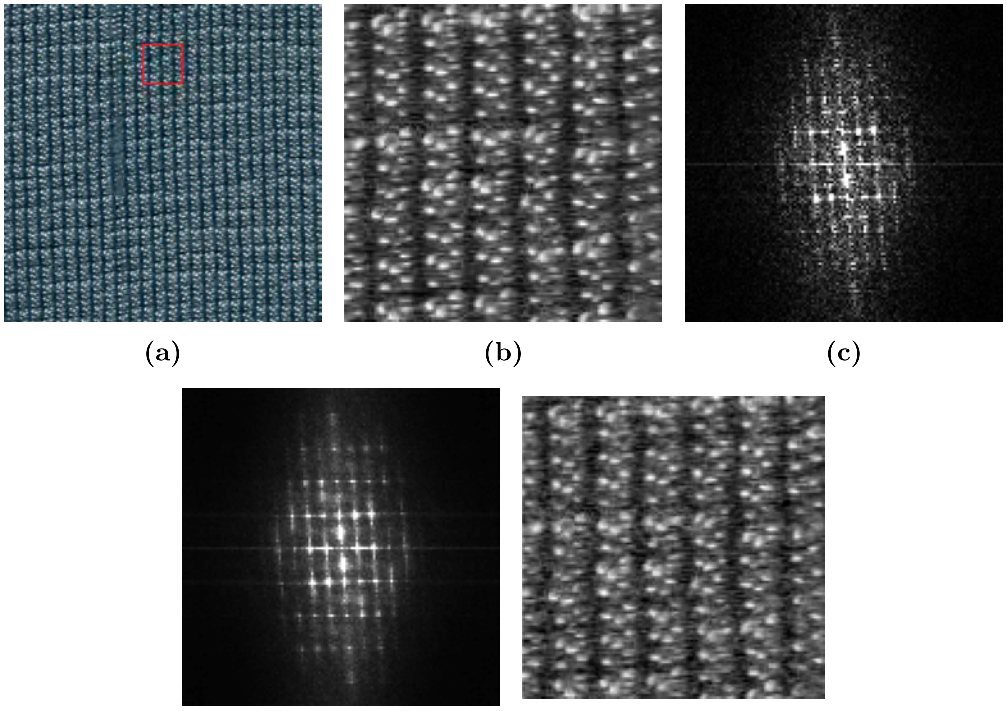
as feature vector. The visualization of magnitude and phase spectrum of Fourier representation of a fabric sample consist of repeated texture from ESTD database given in Figure 3.2.

3.2 Description of The Proposed Algorithm

Textile fabrics categorized as structural texture which can be defined as a repeated pattern based on a certain rules. Any fault or discontinuity in the structural textures cause degradation in its regularity, as seen in Figure 3.3 where a defect in left bottom part of the sample image led to a degradation of several local spectrum in same local of FT magnitude images. Regularly repeating patterns accumulates peaks around related frequency components in the Fourier spectrum of input image, unless any defected texture deteriorate those components in the spectrum. Therefore, frequency domain analysis is frequently employed in defected fabric detection.

Majority of the methods either require a training step which aims to construct or learn a model from clean fabric or directly employ a defectless sample of fabric as reference. Since different fabrics have different models, supervised approaches decrease comfort and convenience. In this thesis a novel unsupervised method that works without a training step and without need to a clean texture reference proposed. The approach have more accurate results compare to state of the art. Furthermore, the only parameter to be tuned is a single distance threshold value in the method.

In the proposed method, instead of utilizing features extracted from single clean fabric texture as reference, *a reference spectral representation* $(\check{F})$ from each inspected fabric image itself extracted. Spectral features obtained from a defectless fabric insufficient to present and amplify the basic features of repeated structures that is necessary in reference features as visualized in Figure 3.4. Besides, it is not



(a) (b) (c)

(d) (e)

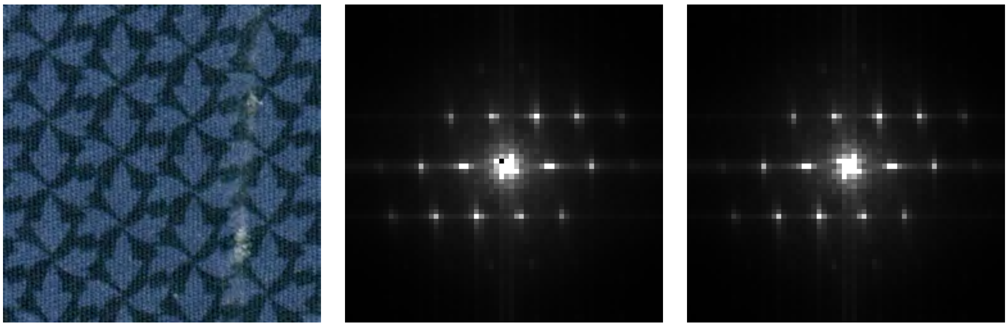
Figure 3.4: *(a) Defected fabric sample. (b) Defect free patch* 128×128 *marked in red in (a). (c) Magnitude of Fourier representation of patch in (b). (d) Fourier representation of refined reference of fabric in (a). (e) Reconstructed image by inverse Fourier Transform using refined Fourier magnitude and phase information of defect free patch in (b).*

possible to obtain a noise free reference image from real fabric images. Therefore, a reference spectral representation acquired from the patches of the inspected image (see Figure 3.4d).

To obtain a reference spectral representation, a gray level input image of $M \times N$ pixels divided into a grid of non-overlapping $m \times n$ pixels patches. After that local frequency spectrum of each patch via 2D Fast Fourier Transform (FFT) computed.

$$F_{k,l}(u,v) = \sum_{x=1}^{m} \sum_{y=1}^{n} f(x,y) e^{-j2\pi(ux/m \ + \ vy/n)} \tag{3.8}$$

where (x, y) and (u, v) coordinates in spatial domain and spectral domain, respectively. FT of grid of pixel patches utilized instead of global FT because in global Fourier analysis small faults will have almost no impact on the Fourier component hence will be terribly difficult to detect. Even if a defect found in using global FT, it can not be localized. The Fourier component given by $F_{k,l}(u, v)$ is a complex number which contains real and imaginary part of local frequency spectrum for $[k^{th}, l^{th}]$



(a) **(b)** **(c)**

Figure 3.5: *(a) Defected fabric sample. (b) Fourier spectrum magnitude image of reference representation. (c) Fourier spectrum magnitude image of refined reference representation.*

patch of input image.

$$F_{k,l}(u,v) = \Re(F(u,v)) + j\ \Im(F(u,v)) \tag{3.9}$$

where $\Re(F)$ and $\Im(F)$ are real and imaginary components of the frequency spectrum.

To obtain the representation of repetitive texture information from the complex Fourier output, magnitude of local spectrum need to be extracted. As where $F_{k,l}(u,v)$ is the local frequency spectrum and $FM_{k,l}(u,v)$ is the magnitude of local frequency spectrum

$$FM_{k,l}(u,v) = |F_{k,l}(u,v)| \tag{3.10}$$

For an $M \times N$ image and $m \times n$ non-overlapping patches, the total number of patches become $p \times q$ in the grid where $p = M/m$ and $p = N/n$.

To obtain the reference spectral representation, the mean of magnitudes of all local spectra in the grid simply calculated as:

$$\bar{F}(u,v) = \frac{\sum_{r=1}^{p}\sum_{r=1}^{q} FM_{k,l}(u,v)}{p \times q} \tag{3.11}$$

When the mean of local spectrum magnitudes of all patches obtained as $\bar{F}(u,v)$, it was understood that defected patches contributed as much as defect free patches in the reference representation. Defected patches in the first reference converge to the average image as shown in Figure 3.5b, where a black hole appeared in the middle of the first reference image. A single step refinement operation applied by calculating another average after eliminating outliers (presented in Figure 3.5c).

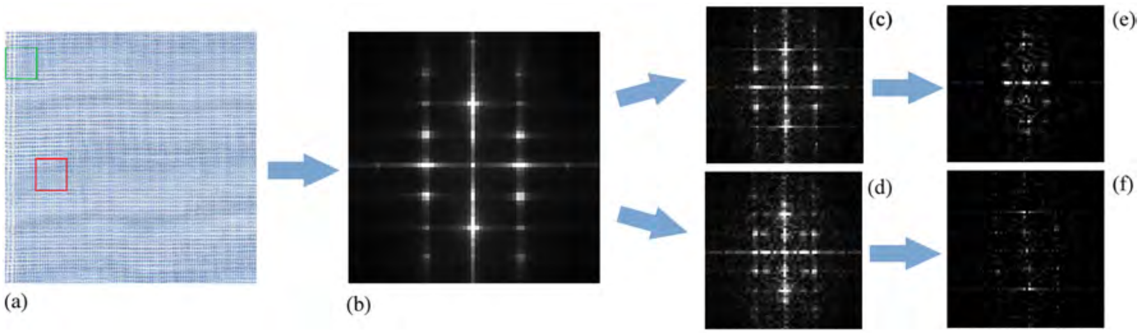


Figure 3.6: *(a) Fabric sample. (b) Refined reference spectral representation of (a) using* 64×64 *patch size. (c) Spectral representation of* 64×64 *defected green window in (a). (d) Spectral representation of* 64×64 *defect free red window in (a). (e) Difference matrix of defected patch* $\Delta(u,v)$ *between (b) and (c). (f) Difference matrix of defect free patch* $\Delta(u,v)$ *between (b) and (d).*

To detect outliers, difference matrices $\Delta_{k,l}(u,v)$ calculated between $\bar{F}(u,v)$ and spectrum of each local patch in the grid. The residual matrix of defected patch have more pixel values (remains) than the matrix resulted from defect free window, sample for each case presented in Figure 3.6.

$$\Delta_{k,l}(u,v) = \bar{F}(u,v) - FM_{k,l}(u,v) \tag{3.12}$$

Variance (σ^2) of each $\Delta(u,v)$ matrix calculated as a scalar estimate for the distance between each local spectrum to the reference spectral representation.

$$\sigma^2_{\Delta_{k,l}} = \frac{\sum\limits_{u=1}^{m}\sum\limits_{v=1}^{n}[FM(u,v) - \bar{F}(u,v)]^2}{m \times n - 1} \tag{3.13}$$

Once the variance of each local spectrum's difference matrix ($\Delta_{k,l}$) obtained, it can be proceed to obtain a refined spectral representation $\check{F}(u,v)$. For this purpose, the variance values sorted in ascending order and the average of the corresponding $FM_{k,l}(u,v)$ matrices in the first half of the sorted list is calculated. The calculation of average matrix is identical with the computation in Eq.3.11. In this manner, half of the local spectra which differs from $\check{F}(u,v)$ eliminated as their difference matrices yields a respectively large variance.

After the computation of refined reference spectral representation ($\check{F}(u,v)$) (shown in Figure 3.5c), there remains too less to detect whether the image is defected or not.

Besides the extracted patches for the computation of $\check{F}(u,v)$, extra patches are extracted from intersecting locations of previously extracted ones. In this way, defects which may exist around the boundaries of non-overlapping image patches are prevented to be missed. After all patches in the image are extracted in a 50% overlapping manner and have their magnitudes of their Fourier spectra computed; the variances (σ^2_Δ) of $\Delta(u, v)$ which is the difference matrix between $\check{F}(u, v)$ and $F(u, v)$ are checked. Then by comparing σ^2_Δ with a empirically determined threshold value, a decision made whether the patch is faulted or not. Thus, not only the defected fabrics detected, also the defects can be located with the resolution of patch size.

4. DATASET

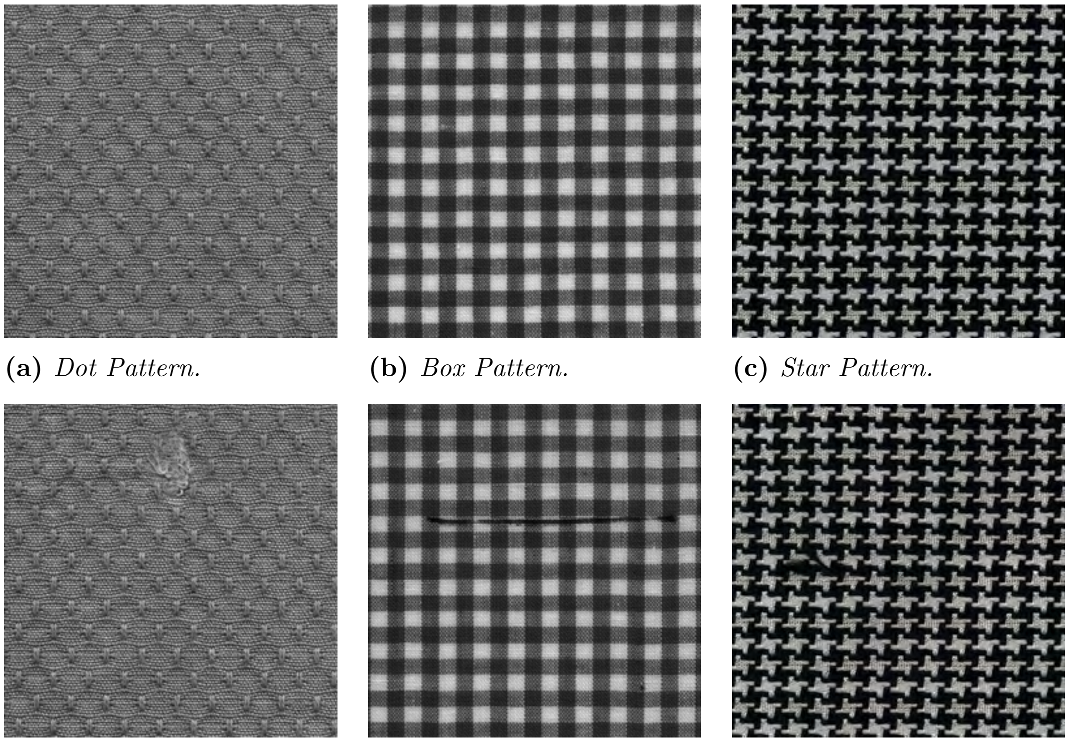
4.1 Review of Existing Datasets

Although detection of faults in textile fabrics is an active research area, available dataset for this purpose are very limited. TILDA [30] is one of the earliest datasets constructed for textile fabrics by a working group on texture analyzing of the Deutsche Forschungsgemeinschaft Germany. It contains 3200 images, totally 8 kinds of fabric with seven error classes included in addition to defect free class. Although it has large number of images, all images are gray scale which makes it unsuitable for RGB based algorithms. Moreover with 7 defect classes it has limited range of defect types and the dataset is not free for use. Some researchers like Maenpaa et al. [7], Chetverikov et al. [29] and Susan et al. [32] used datasets designed for texture recognition and classification (like Outex [47] and Brodatz [31]). The authors extracted the few number of textile fabric images within those datasets and used it for textile inspection purposes.

The only freely available dataset for this purpose, to our knowledge, is created by researchers H.Y.T. Ngan and G.K.H. Pang in Industrial Automation Research Laboratory, The University of Hong Kong [1]. The database has three different pattern fabric images (Dot, Box and Star patterns) shown in Figure 4.1. It consist of:

- 30 defect free and 30 defected samples of Dot pattern.
- 30 defect free and 26 defected samples of Box pattern.
- 25 defect free and 25 defected samples of Star pattern.

The defects in the dataset are as follows: broken end, hole, knot, netting multiple, thick bar and thin bar. Ground truth for each image provided as regions with white pixels indicating defected regions while black pixels indicating clean regions. Besides the insufficient number of the images and defect classes, some of the defects are handmade as declared by the authors. Therefore, available datasets are very limited in terms of both number of images and defect types.



(a) *Dot Pattern.* (b) *Box Pattern.* (c) *Star Pattern.*

(d) *Knot Defect.* (e) *Thin Bar Defect.* (f) *Broken End Defect.*

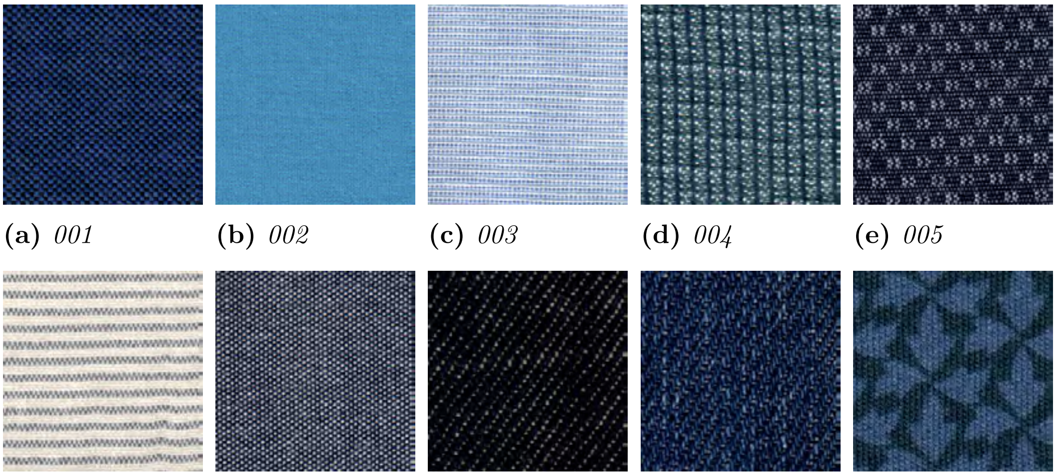
Figure 4.1: *Defect free (a,b,c) and defected (d,e,f) fabric samples from [1] dataset.*

4.2 Eskisehir Technical University Textile Defect Dataset (ESTD)

In this part, a novel textile fabric dataset introduced for empirical evaluation of fabric defect algorithms. The images belong to 10 type of different structure fabrics shown in Figure 4.2.

Fabrics acquired from textile factory, hence 90% of the faults are real but some handmade defects included like (holes, stains, etc.). Dataset was generated by scanning images as RGB in 300dpi. obtained images partitioned into 10% overlapping patches. The reason for overlapping is to include any defect may fall in the borders. There are 2969 images totally, 2231 of them defect free and 738 defected. There is variation in number of samples for each fabric type and defect class. Ground truth for the images are provided as 16×16 pixel regions, if the region is faulted denoted by 1 ,otherwise, denoted by 0. Regions of size 16×16 chosen because it is the best size to fit the small defects in our samples. The size of images are 256×256 pixel in *.PNG* format.

Overall defect types in the dataset are 27 classes plus a clean class. Existent defect classes are the most widespread types in the industry (see Table 4.1 for defect



(a) *001* **(b)** *002* **(c)** *003* **(d)** *004* **(e)** *005*

(f) *006* **(g)** *007* **(h)** *008* **(i)** *009* **(j)** *010*

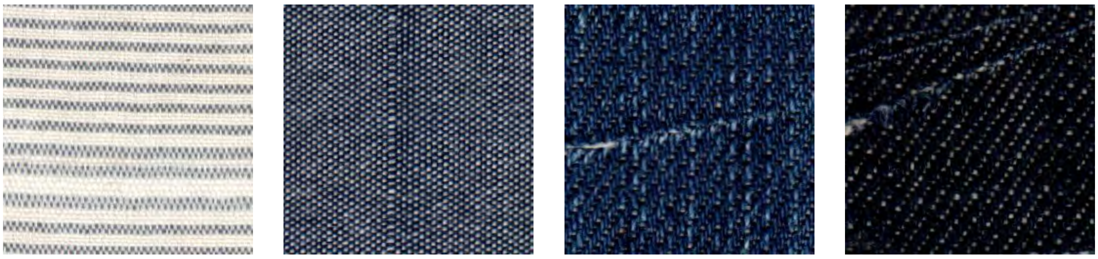
Figure 4.2: *Ten types of defect free fabrics used in our dataset with their id numbers.*

classes with their description [17] and an illustration for each one). These faults occur in different stages of fabric manufacturing. Some of them happens during the weaving or knitting stage like (miss end, coarse end, double pick, warp float, etc.). While other faults happens in the dying stage like (dye spot) and in the last folding or storing stage defect like (pin mark, knot, hole, etc.) may appear. The faults occur mostly due to technical issues.

Textile fabrics are categorized as uniform texture [2] which can be defined as a pattern or texture repeated based on some rule (or fixed distance). Fabrics consist of two set of threads, horizontal threads called warp and vertical ones called weft. Occasionally, breaking the regularity in one thread will affect the neighbor threads and this lead to more than one fault in an image like weft direction defects in Figure 4.3c and warp direction defects in Figure 4.3b. There are some defects that are very related to each other i.e the occurrence of one leads to or followed by the other most of the time This kind of abnormalities considered a technical problem by the manufacturers. As shown in Figure 4.3, loopy filling defect appears more frequent with some specific defects like smash defect (in Figure 4.3c, and in Figure 4.3d).

Generally, the dataset contains various structured fabrics. The plain or unpatterned fabrics (shown in Figures 4.2a, 4.2b, 4.2c and 4.2g) has the highest production rates therefore, 40% of the dataset consist of plain textures. The other 36% of the images are patterned textures (shown in Figures 4.2d, 4.2e, 4.2f and 4.2j). The last 24% consist of two types of denim fabrics (shown in Figures 4.2h and 4.2i) which is not included in any other dataset before to be best of our knowledge.

Finally, ESTD database created to be a general reference dataset for developers

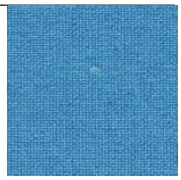
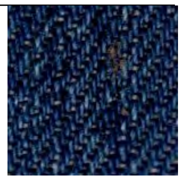


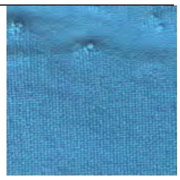
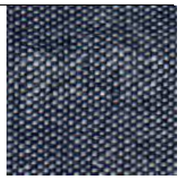
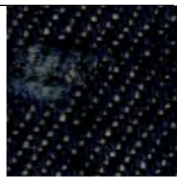
(a) *Thin pick & Double pick* (b) *Coarse end & Thin end* (c) *Smash & Loopy filling* (d) *Smash & Loopy filling*

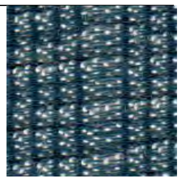
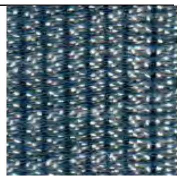
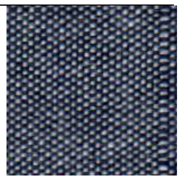
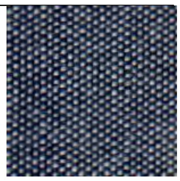
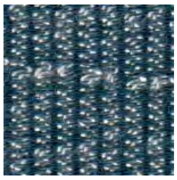
Figure 4.3: *Defected samples that contains more than one fault from ESTD dataset.*

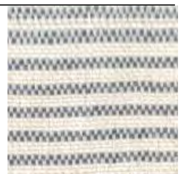
to investigate their methods ability, evaluate and compare their approaches in an objective matter and in universal platform. Fabric patterns gathered for the database insured to contain distinct kind (patterned, plain and denim) to be convenient for various methods. High number of samples respectively and small overlapping ratio will allow the dataset to utilized by deep learning systems.

Table 4.1: *Defect description in ESTD dataset.*

Defect name	**Defect type**	**Defect description**	**Example**
Hole	Common to both warp and weft	A fabric area free of yarn.	
Rust/dirt Stain	Common to both warp and weft	A fabric area contains stain or a dirt.	
Oil stain	Common to both warp and weft	A fabric contains oil spot.	
Dye spot	Common to both warp and weft	A variation in color or dye spot found in fabric.	

Defect name	Defect type	Defect description	Example
Pin mark	Common to both warp and weft	A fabric contains holes along selvage.	
Slub	Common to both warp and weft	Thick or heavy place in yarn.	
Knot	Common to both warp and weft	A place where two ends of yarn have been tied together, and the tails of the knot are protruding from the surface.	
Knot with halos	Common to both warp and weft	A knot with halo surrounding area (variation of color).	
Loopy filling	Common to both warp and weft	A group of fibers hang out above the yarn.	
Corrugation	Common to both warp and weft	A fabric contains wavy areas.	
Smash	Common to both warp and weft	Many warp and fill threads are broken.	
Birds eye	Warp direction defect	Two small distorted stitches or holes side by side.	

Defect name	Defect type	Defect description	Example
Open reed	Warp direction defect	Warp threads is held apart exposing the filling yarn.	
Miss end	Warp direction defect	An absent of one warp threads.	
Warp float	Warp direction defect	A portion of yarn in a fabric that extends or floats over two or more adjacent ends.	
Double end	Warp direction defect	A present of two warp threads instead of one side by side.	
Coarse end	Warp direction defect	A warp thread is twice size (or more) of the normal thread.	
Irregular warp density	Warp direction defect	Irregular or uneven warp thread density.	
Thin end	Warp direction defect	The diameter of a warp thread is thinner than others.	
Shed split	Weft direction defect	Splitting the shed and passing over certain warp ends of this four-harness weave. It shows up as short filling floats on the face and corresponding warp floats on the back of the fabric.	

Defect name	**Defect type**	**Defect description**	**Example**
Gouts	Weft direction defect	Thick or heavy place in yarn, differ from slubs in that they are characterized by a lumpy appearance while slubs generally are symmetrical.	
Double pick	Weft direction defect	A present of two weft thread instead of one side by side.	
Miss pick	Weft direction defect	An absent of one weft thread.	
Weft float	Weft direction defect	A portion of yarn in a fabric that extends or floats over two or more adjacent picks.	
Coarse pick	Weft direction defect	A weft thread is twice size (or more) of the normal thread.	
Thin pick	Weft direction defect	The diameter of a weft thread is thinner than others.	
Irregular weft density	Weft direction defect	Irregular or uneven weft thread density.	

5. RESULTS

In the first part of this chapter, existing datasets in literature have been reviewed and a new dataset is proposed. Then the effect of patch size of the proposed approach on the detection results discussed. Finally, comparative experimental results of proposed method with the latest and best two methods in literature are provided.

5.1 Effect of Window Size

There are several parameters that effect the detection rate and localization of defects. Window size selection is one of the major factors in most algorithms. Therefore, Amelung and Vogel [48] examined and compared the effect of changing window size with different feature extraction methods. Also, there is window size selection algorithms [32] to choose an optimal size based on the fabric pattern inspected.

In this work, various patch size examined in order to contain the repeating pattern several times to have a more meaningful spectral representation. The selected size should not be too big because small defects will not be significant in the spectral representation. As a performance criteria, Accuracy calculated as:

$$Accuracy = \frac{TP + TN}{Total\ Number\ of\ Samples} * 100\% \tag{5.1}$$

Where TP and TN represents true positives and true negatives respectively. Window size test result on Dot, Box and Star patterns dataset shown in Table 5.1 and on ESTD dataset shown in Table 5.2. The number of samples in each fabric type is unequal, therefore all the averages mentioned in this study are weighted averages.

When using window size 64×64, the accuracy is 83.66% in ESTD and 87.39% in Dot, Box and Star patterns database. While when decreased the window size, the

Table 5.1: *Patch size effect on accuracy results on Dot, Box and Star patterns dataset.*

Fabric type	**Patch size**		
	64 × 64	**32 × 32**	**16 × 16**
Dot	95.00	100.0	100.0
Box	80.36	87.50	64.28
Star	86.00	94.00	96.00
Average	**87.39**	**94.00**	**86.88**

detection rates increased in both datasets. This is because small defects may not appear using big window size. When window size 16×16 used the overall accuracy decreased. Because the small patch size led to miss the texture of the fabric hence the average image was not the optimal representer of that texture, as observed in big patterned fabrics like 4.2d, 4.2e and 4.1c. Besides, some big defects may cover all the 16×16 region (i.e. defect in 4.3c).

Highest detection rates was obtained using 32×32 window size in both datasets. Window size besides the accuracy and localization of defect, effects the computational time of the algorithm. When using window size 64×64 the execution time is $112ms$, while using window size 32×32 the time is $118ms$ and using window size 16×16 the time is $184ms$. Execution time is increased when decreasing the window size. By considering accuracy, localization and execution time results obtained from experiments on two datasets, the best patch size proven to be 32×32 and used in posterior experiments in this thesis.

Table 5.2: *Patch size effect on accuracy results on ESTD dataset.*

Fabric type	**Patch size**		
	64 × 64	**32 × 32**	**16 × 16**
001	82.47	83.77	88.96
002	91.91	94.12	97.06
003	78.47	76.39	78.47
004	87.63	91.16	86.87
005	79.09	84.54	77.27
006	68.12	66.09	66.09
007	86.58	88.42	89.34
008	85.11	86.63	86.63
009	86.38	86.65	86.38
010	85.53	85.96	87.28
Average	**83.66**	**84.87**	**84.84**

5.2 Quantitative Results

In this section, the performance of proposed algorithm evaluated and compared with two of the recent methods in this field which are ER method [12] and ID method [6]. Two databases used in experiments i.e. ESTD and Dot, Box and Star patterns [1].

Table 5.3: *Accuracy results for each type of fabrics in ESTD database.*

Fabric type	Algorithm		
	ID [6]	**ER** [12]	**Proposed**
001	70.78	83.22	**83.77**
002	**94.85**	94.66	94.12
003	75.00	**78.42**	76.39
004	79.80	90.79	**91.16**
005	69.09	79.05	**84.54**
006	59.42	61.47	**66.09**
007	77.11	77.48	**88.42**
008	77.20	85.18	**86.63**
009	82.56	84.53	**86.65**
010	77.19	85.65	**85.96**
Average	**76.18**	**80.93**	**84.87**

In total 3135 fabric images utilized, 2969 images from ESTD database and 166 from Dot, Box and Star patterns database. All images are in size 256×256. Experiments held on an Intel i7 2.40GHz processor, 16GB RAM laptop computer. As programming language, MATLAB R2018a used.

Main goal of the approach is to design an algorithm that work independently from fabric paterrn type and defect type. Proposed method utilized frequency domain features that can represent all kind of fabrics regarding their pattern (plain or motif based). As we discussed the effect of changing window size on detection result and issues related with pattern size, we can proceed with window size 32×32.

Because of this research area is mostly employed for industry sector, it was very difficult to find methods to compare proposed approach, the only available methods were ER and ID. ER algorithm has 5 parameters that needs to be tuned. In the method, training stage utilizes 5 defect free image sample from tested fabric class to obtain min and max threshold. In testing stage, obtained thresholds with the 5 parameters used in detection.

ID algorithm has parameters not only for different fabric classes but for each defect class. Since ESTD has 27 defect class it was not possible to find best parameters for each class therefore, parameters specified for various fabric types examined only. Both ER and ID algorithm provides a black and white image, where white pixels considered as faulted area while black pixels considered as clear area. For this reason number of white pixels counted and used in decision if the image is defected

Table 5.4: *Accuracy results for each type of fabrics in dataset [1].*

Fabric type	Algorithm		
	ID [6]	**ER** [12]	**Proposed**
Dot	80.00	89.58	**100**
Box	76.47	84.44	**87.50**
Star	55.56	85.71	**94.00**
Average	**71.42**	**86.70**	**94.00**

or defect free.

Empirical results given in Table 5.3 for ESTD dataset and in Table 5.4 for Dot, Box and Star dataset. It can be seen that the proposed method is more accurate except for two types of fabrics and it has best overall accuracy for all datasets.

In terms of running time, proposed method performs about 0.12 seconds per image while ER method works about 1.63 seconds and ID method works about 1.82 seconds in average for the same image in our dataset. As understood proposed algorithm execute faster than both of state-of-art methods, hence it could be utilized for both online and offline inspection.

Visually results are presented in Figure 5.1 for all three algorithms using fabric image samples from ESTD dataset.

5.3 Discussions

The main objective of every defect detection algorithm is to find the sample that differ from a template image. For this purpose various techniques has been introduced, moving subtraction is one of them. Yazdi and King [49] performed subtraction method for lace fabric inspection. They subtracted an inspected lace from a reference template. But for direct subtraction, the two images need to be comparable mean they are aligned and in same scale. Nevertheless aligning every inspected image is not practical and time consuming. Also there is vey difficult textures that make the alignment process impossible. After that Ngan et al. [11] utilized three algorithms involving subtraction idea. As reviewed before, all three methods combined subtraction with Wavelet Transform to improve the detection results and overcome the handicaps faced by Yazdi and King approach. For this reason, translation invariant features like Fourier Transform is highly necessary before performing subtraction or any other technique.

False positive and false negative detections are a serious obstacles in textile inspection algorithms. False negative rates could be reduced by decreasing the threshold used in most methods. One way to avoid false positives is to increase the threshold but this led to miss some small size faults. Therefore, diverse algorithms used to confirm detection outcomes and presence of the irregularities without missing any other ones. That is why Malek [17] proposed an optimization technique using level selection filters. The main idea of filters is to count how many times the defected area will appear in the 4 filters. If a defect seen in more than 2 filters that mean the defect is there. But as seen in the work the filters did not affect the detection rates very much.

In the proposed method, confirmation of irregularities presence performed by 50% overlapping technique. That means the patches move half of the window size in every step. Because of the overlapping ratio, every location scanned four times for faults, Which give a different perspective of the specific defect. Also, by implementing 50% overlapping technique there was no extra process required which could be time consuming.

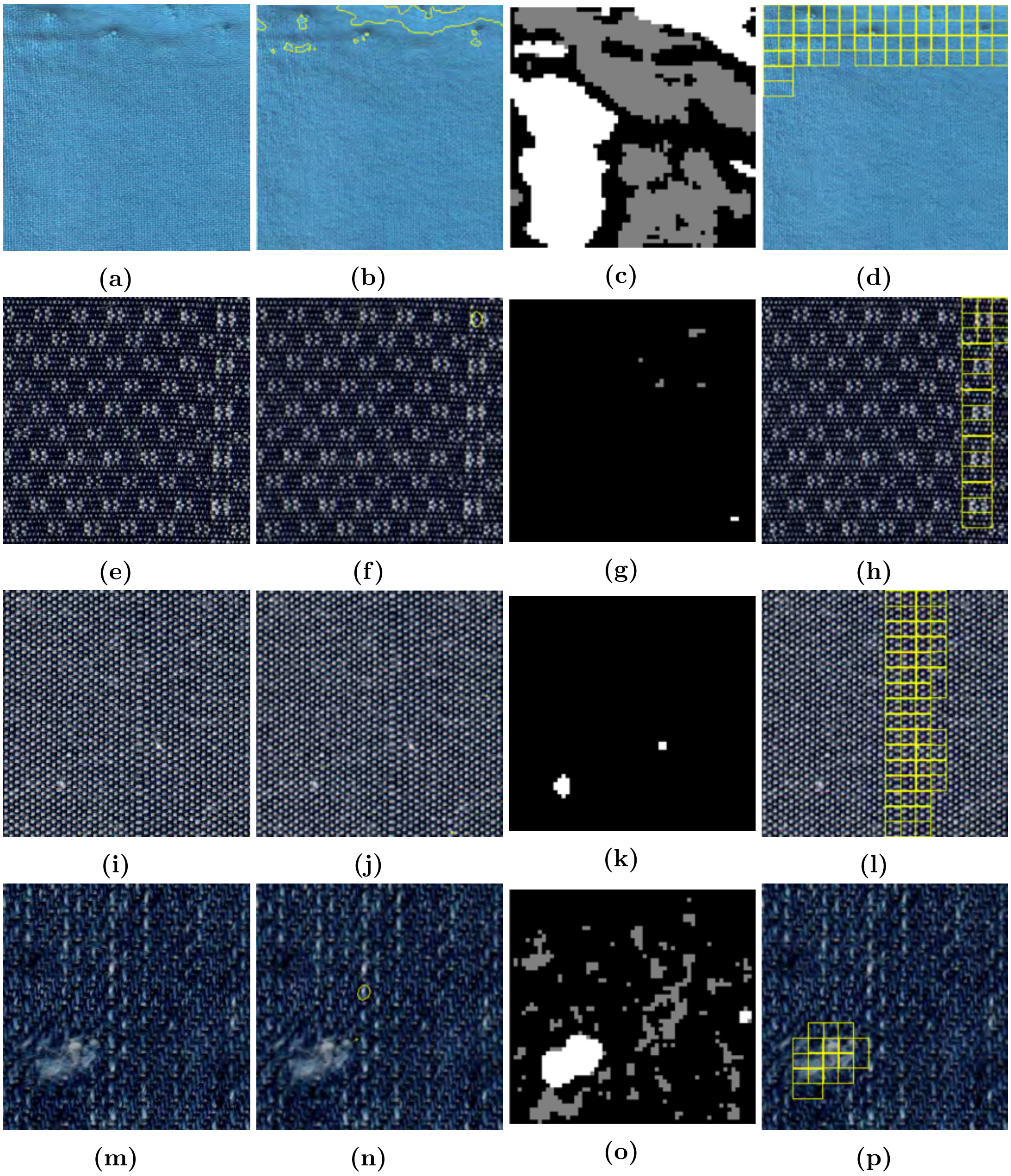


Figure 5.1: *Visual results of proposed method and compared two methods. Where first column is the defected image, second column ID method results, third column ER method results and last column is the results of proposed method.*

6. CONCLUSION

In this thesis, an unsupervised and robust method for defect detection in textile fabric images proposed. The proposed approach is based on local spectra representation of the repetitive pattern of the fabric textures. The reference image is extracted from the local spectra of the inspected image, without requiring any defect free image of each separate fabric type. Therefore, proposed method more adaptive to the intra-fabric variations as well as rotation or translation of the image. As a result of using local spectral, each defect inspected and detected simply.

Proposed algorithm tested on two different datasets with overall 3135 samples. High detection rate up to 94% obtained by the proposed method compare to state-of-art methods with detection rates up to 86.70% and 71.42% for ER and ID methods, receptively. All three algorithms need one parameter for selecting the threshold value manually.

There is a demand on parameter-free methods specifically in industrial fields. The future plan is to optimize the algorithm to select the threshold value automatically. Diversity of fabrics and large number of defect types hinders the practical utilization of these systems due to the need for parameter tuning. In addition to detection of defected fabrics, also there is plans to improve algorithm to recognize defect types as well in the next step of the study.

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