Computer Vision-based Fabric Defect Detection: A Survey

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Abstract

The investment in automated fabric defect detection is more than economical when reduction in labor cost and associated benefits are considered. The development of fully automated web inspection system requires robust and efficient fabric defect detection algorithms. The inspection of real fabric defects is particularly challenging due to the large number of fabric defect classes which are characterized by their vagueness and ambiguity. Numerous techniques have been developed to detect fabric defects and the purpose of this paper is to categorize and/or describe these algorithms. This paper attempts to present the first survey on fabric defect detection techniques presented in about 160 references. Categorization of fabric defect detection techniques is useful in evaluating the qualities of identified features. The characterization of real fabric surfaces using their structure and primitive set has not yet been successful. Therefore on the basis of nature of features from the fabric surfaces, the proposed approaches have been characterized into three categories; statistical, spectral and model-based. In order to evaluate the state-of-the-art, the limitations of several promising techniques are identified and performances are analyzed in the context of their demonstrated results and intended application. The conclusions from this paper also suggest that the combination of statistical, spectral and model-based approaches can give better results, than either one individually, and is suggested for further research.

Keywords: *Quality Assurance, Industrial Inspection, Fabric Defect Detection, Automated Visual Inspection, Textile Inspection*

1. Introduction

Inefficiencies in industrial process are costly in terms of time, money and consumer satisfaction. The global economic pressures have gradually led business to ask more of itself in order to become more competitive. As a result, intelligent visual inspection systems to ensure high quality of products in production lines are in increasing demand. The raw materials for many of the finished consumer products are available in the form of web[1] materials. Industrial web materials take many forms but there is a remarkable similarity in automation requirements for visual inspection of these materials. As shown in Fig. 1, automation problems for web inspection falls into two general categories based on the types of web materials [21]. The first category of problems are associated with uniform web materials such as metals, film, paper, *etc*.. Defect detection in these web materials normally relies upon identification of regions that differ from a uniform background. The second category of web inspection problems are associated with textured materials such as textile, ceramics, plastics, *etc*.. The perception of what constitutes to be a textured defect varies from individual to individual and often one individual may have different sensitivity from time to time [8]. The characterization of defects in textured materials is generally not clearly defined. Therefore the visual inspection of textured materials consists of grading the materials based on the overall texture characteristics such as material isotropy, homogeneity and texture coarseness.

The textured materials can be further divided into uniform, random, or patterned textures. Brazakovic *et al.* [22] have detailed a model-based approach for the inspection of random textured materials. The problem of printed textures (*e.g.* printed fabrics, printed currency, wall paper) requires evaluation of color uniformity [153] and consistency of printed patterns, in addition to any discrepancy in the background texture, but has attracted little attention of researchers. This paper [1] is focused on the inspection of uniform textured materials and presents a survey on the available techniques for the inspection of fabric defects. The inspection of real fabric defects is particularly challenging due to the stochastic variations in scale, stretch and skew of fabric texture/defects predominantly due to the environment and the nature of weaving process.

[1] The term *web material* refers to the materials produced in the form of continuous rolls.

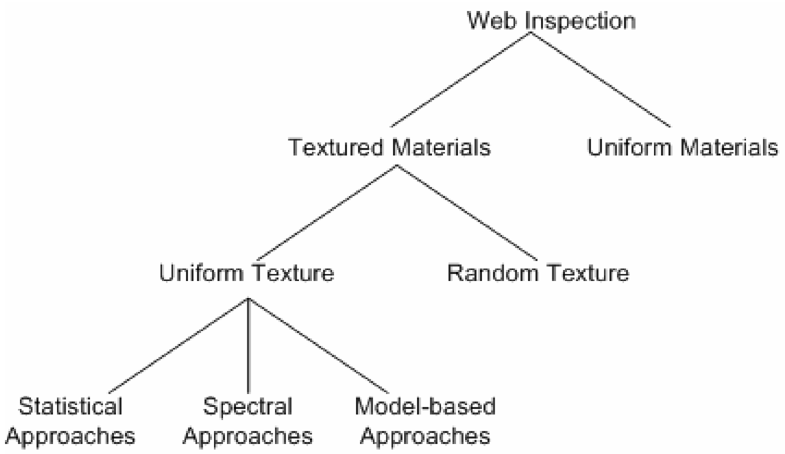

Figure 1 : Classification of inspection problem based on material types.

1.1 Fabric defects

It has been estimated [26] that the price of fabrics is reduced by 45%-65% due to the presence of defects. The fabric quality is affected by yarn quality and/or loom defects. The poor quality of raw materials and improper conditioning of yarn result in yarn quality defects and effects such as color or width inconsistencies, hairiness, slubs, broken ends, *etc*.. There are numerous quality tests for yarns, such as ASTM D2255-96 [27], for predicting the quality of fabric to be produced from the entire lots of sampled yarns. The tests on the quality of yarns are usually performed at the output of spinning-mills.

Quality test runs for looms and knitting machines require interruption of the weaving process [28]. This interruption is not practically feasible for the machines that are intended for large production runs of fabric rolls. The quality test runs on the older, worn, or obsolete model weaving machines generally produce unacceptable results. These test runs tend to be smaller and may not register recurring fabric defects that are generated due to sinusoidaly occurring inconstancies in the weaving machines. Therefore, such fabric defects can be incorrectly read as resulting from poor yarn quality. The fabric defects resulting from variations in the tension of one or more yarn strands are generally misread as the defects resulting from poor yarn quality. The weaving irregularities generated in the weaving machines due to the change in operating conditions (temperature, humidity, *etc*.) also result in various fabric defects independently of yarn quality. The population of fabric defects may vary dynamically as small changes in the weaving process can result in entirely new class of fabric defects.

1.2 Traditional inspection

There are two distinct possibilities for fabric defect detection. The first possibility is the process inspection in which the weaving process (or its parameters) can be constantly monitored for the occurrence of defects. Process inspection is a preventive inspection, and is generally not performed in the textile industries due to the complexity of the weaving process. The second possibility is the product (end) inspection in which the manufactured fabric has to be inspected for the defects. The present research is focused on product inspection.

The fabric produced from the weaving machines is about 1.5-2 meters wide, and rolls out at the speed of 0.3-0.5 meters per minute. The product inspection in the textile industries is not performed concurrently with the production. The slow speed of manufactured fabric is insufficient to keep a human inspector occupied and human inspection is therefore uneconomical. Also, the relatively hostile working environment [20] near the weaving machines is not suitable for human inspection. The traditional inspection procedure is to remove the manufactured fabric rolls from the weaving machines and unroll them on the inspection table (specially illuminated) at a relatively higher speed of 8-20 meters per minute. When a human inspector notices a defect on the moving fabric, he stops the motor that moves the fabric roll, records the defect and its location, and starts the motor again. The early detection of repetitive defects and extraordinary defect rate is left to the operators or so called *roving inspectors* [29]. These *roving inspectors* will warn the production department so that appropriate measures can be taken to decrease the defect rate.

2. Automation for inspection

The automation of visual inspection process [2] is a multifaceted problem and requires complex interaction among various system components. Nickolay *et al*. [10] have shown that the investment in the automated fabric inspection system is economically attractive when reduction in personnel cost and associated benefits are considered. The architecture of a typical automated textile web inspection system is shown in Fig. 2. The system consists of a bank of cameras arranged in parallel across the web to be scanned, a computer console hosting (single or an array of) processors, the frame grabber, a lighting system and the supporting electrical and mechanical interfaces for the inspection machine. The inspection system employs massive parallelism in

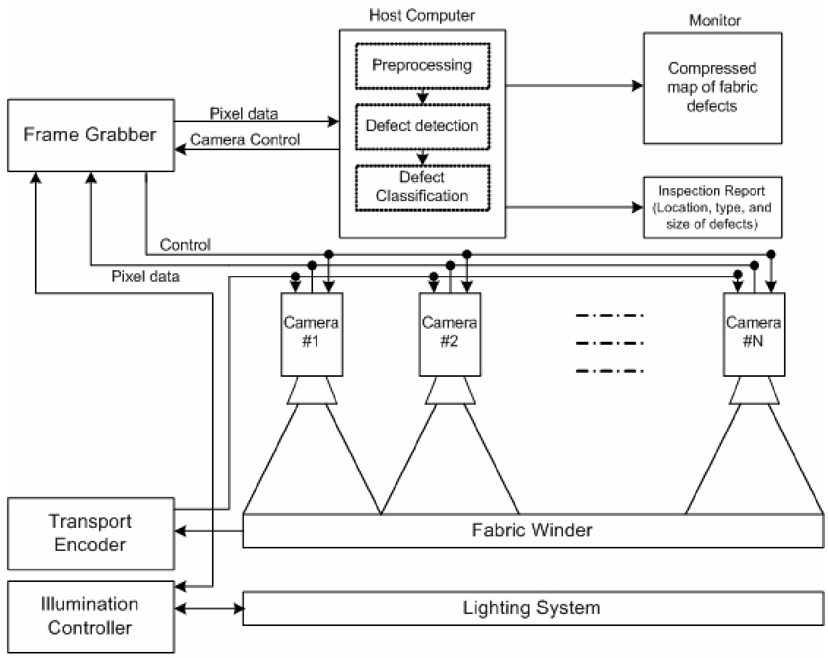

Figure 2 : Architecture of a typical automated visual inspection system for textile web.

image acquisition with a front-end algorithm that reduces the data flow to the region of interest only. The key components of this system are briefly reviewed below:

Lighting system: The quality of acquired images plays a vital role in simplifying an inspection problem. The image quality is drastically affected by the type and level of illumination. Bachelor [30] has performed a comprehensive study of various lighting schemes for automated visual inspection. There are four common types of lighting schemes used for visual inspection *i.e.* front, back, fiber-optic, and structured. The backlighting eliminates the shadow and glare effects, and is used for fabric inspection. It is also possible to employ fiber optic illumination for the fabric inspection, as it provides uniform illumination of products without any shadow or glare problem. However, fiber-optic illumination is most expensive to realize and is not economical for 6-8 feet wide textile webs. A fuzzy logic control scheme using a feedback photo-resistor is sometimes used by the illumination controller to maintain a constant (within 1%) level of illumination [31].

- **Camera**: A large variety of cameras with tremendous difference in sensor types, resolution, read out speed, accuracy and other features find their applications in the machine vision [32]. The resolution of a camera is limited by the number of pixels in the camera photosensor and the object Field of View (FOV). The FOV is dependent on the characteristics of the background and the nature of defects to be detected.

There are two common types of scanning techniques employed for the fabric inspection cameras: line scanning and area scanning. The line scanning techniques utilize a system of linear array photosensors, and the resolution in the vertical direction is a function of the velocity of object (web) movement and the scan rate (line rate) at which the camera is operating. The modern line scan cameras usually provide very high resolution and can inspect a large portion of textile web in the single line scan. A transport encoder is always required for all line scan cameras to ensure synchronization of the camera scan rate with the transport velocity [33]. The disadvantage with the line scan cameras is that they do not generate complete image at once and requires external hardware to build up images from multiple line scans. For area scan cameras, the usage of transport encoders is optional and the inspection resolution in both directions is independent of object (web) speed. At present, the cost of a line scan camera is very high and therefore an array of area scan cameras is commonly used to provide economical solutions for the web inspection problem. The state-of-the-art for the line scan and area scan cameras is available with CCD or CMOS photosensors. The photosensors with CMOS active pixel architecture provide higher level of on-chip functionality at lower cost and low power usage than those from the CCD ones. However the CMOS sensors are generally less sensitive than their CCD counterparts, mainly due to higher uniformity and smaller fill factor. The inspection of fabric defects using CMOS area scan cameras [35], time-delay-and-integration (TDI) line scan cameras [31], [36] have been attempted by researchers.

- **Transport encoder**: The transport encoder is used to provide master timing pulses for the camera. The wheel of the transport encoder is in direct contact with fabric winder. In case of line scan cameras, the resolution of the transport encoder (*i.e.* number of pulses per revolution) determines the pixel resolution. The line scan cameras can acquire crisp images at any speed by slaving camera scan rate to transport velocity [31]. The velocity information from the transport encoder is also used to control any undesirable variation in the speed of shaft rollers [35].
- **Frame grabbers**: The pixel data coming from each of the camera is converted into a digitized image by the frame grabber. All web inspection systems, such as the one used for fabric, have to cope with the multiple camera inputs. Some systems do this by using some kind of video multiplexer unit between the camera and

the frame grabber. A rather expensive way to cope with multiple cameras is to use one frame grabber unit per camera [35]. This permits parallel processing of image pixel data if the system is equipped with the multiple processors. The output from the frame grabber is transported to the host computer in any of the popular PC formats (ISA, VESA, PCI, *etc*.) or industrial bus formats (VME, PICMG, PC100, *etc*.).

- **Host computer**: The functions of the host computer can be classified into three main categories. (i) Defect detection and classification: The image data from the frame grabbers is downloaded into the host computer. The host computer is responsible for processing this image data for defect detection using sophisticated algorithms. The defects detected from the acquired image data are classified into several categories depending on their origin or size. (ii) Camera illumination and control: The host computer is responsible for the external loading of control setting parameters of the camera. These parameters are usually loaded at the power-up or operated manually through Graphical User Interface (GUI). The host computer is also responsible for the settings of the illumination controller, which controls the illumination level of web. (iii) System control: The host computer also performs several input and output system control functions. The functions in this category include Interrupt Service Routine (ISR), Graphical User Interface (GUI) and printing/storage of the compressed defect map *etc*..

A single general purpose host computer is insufficient to process high volume of image data acquired to inspect the textile web moving at the speed of 15-20 meters per minute. Therefore most systems use a single separate processor to detect all defects present in images from an individual camera [35]. Each of these processors usually requires additional DSP processors (such as TMS320C40 [36], AT&T 32C [37], *etc*.) for real time implementation of sophisticated defect detection algorithm. Each of the detected defects is classified into one of the several desired categories. Fabric defects are characterized by three types of uncertainty [38]: Vagueness, Incompleteness and Ambiguity. Furthermore, large number of defect classes, inter-class similarity and intra-class diversity of fabric defects form major obstacles in their classification.

3. Prior Literature Review

There have been four surveys of the Automated Visual Inspection (AVI): in 1982 by Chin and Harlow [15], in 1988 by Chin [16], in 1995 by Newman and Jain [3] and Thomas *et al*. [13]. However, to my knowledge, there has not been any literature survey devoted to the fabric defect detection. The prior AVI surveys [15]-[16], [13] [3] could not focus on the inspection of fabric defects, due to their wide coverage on inspection problem. Among these only survey in [3] has included a short paragraph which discusses about the fabric defect detection techniques in six references. The review presented in [13], [15]-[16] has excluded fabric inspection mainly due to their coverage on range of AVI techniques for other industrial products. Moreover, there have been several key developments in AVI technique for fabric defects in last 10 years. In addition, due to rapidly decreasing cost of sensing and computing power, several new algorithms have been proposed for the fabric inspection. The fabric defect detection approaches are not limited to the images acquired from digital camera; Sheen *et al*. [138] have presented an ultrasonic imaging system for textile web inspection, [139] illustrates the use of reflected infrared frequencies while the fabric inspection using the knowledge-based system to trace fabric defects have been proposed in [26], [146], [154].

The literature for fabric defect detection using digital imaging is quite vast. The relevant papers appear in journals and conferences related to computer vision, textile, industry applications, and pattern recognition. The algorithms for the defect detection used in some commercially available systems have not been reported in the literature due to the intellectual property constraints. Therefore the focus of this paper is on the theoretical algorithms developed for the fabric inspection rather than on actual inspection systems. However, only few fabric inspection systems, although very expensive, are currently available in the market and some of these are summarized in [145].

4. A Taxonomy of fabric defect inspection methods

This section presents a review on the prior techniques and models, which researchers have been using for fabric defect detection. At microscopic level, the inspection problem encountered in textured images becomes texture analysis problem. Harlick [41] has used the tone-texture concept to broadly classify the most commonly used texture analysis techniques into two categories: statistical and structural approaches. The pure structural models of image patterns are based on some primitives and placement rules, or tree grammar syntactic approaches [42]. Therefore structural approaches suffer from the complications associated with the determination of the primitives or unit patterns, and the placement rules that operate on these primitives. As a result, the structural approaches for the defect detection have been confined to rather deterministic images such the ones used in printed circuit boards inspection [43], and are not suitable for real textured images such as fabrics. Therefore, broadly speaking all the defect detection techniques presently used are statistical in nature because they employ some form of statistical calculations to declare the defects.

Tuceryan and Jain [44], on the other hand, have identified five major categories of features for texture analysis: statistical, geometrical, structural, model-based and signal processing features. The class of geometrical and structural features extracted for texture analysis assume that the textures are composed of texture primitives or textons. The characterization of textons based on their geometric properties or their placement according to certain placement rules fall in these two respective categories of texture analysis approaches. However these approaches have not been attempted on fabric defect detection, mainly due to the stochastic variations in the fabric structure (due to elasticity of yarns, fabric motion, fiber heap, noise, etc.) which poses severe problems in the extraction of textons from the real fabric samples. Therefore in this paper the proposed defect detection techniques have been classified into three categories: statistical, spectral and model-based. The statistical defect detection methods for textile fabric are firstly introduced in Sec. 4.1., which is followed by spectral approaches in Sec. 4.2. The spectral approaches constitute the largest number of fabric defect detection methods proposed in the literature. The summary of fabric defect detection methods using stochastic model-based texture features is presented in Sec. 4.3. Sec. 5 attempts to classify the scope of some of the proposed methods and their key challenges. Finally, Sec. 6 summarizes the conclusions from this paper.

4.1 Statistical approaches

The objective of defect detection is to separate inspection image into the regions of distinct statistical behavior. An important assumption in this process is that the statistics of defect-free regions are stationary, and these regions extend over a significant portion of inspection images. The pure-statistical approaches form the majority of work presented in the literature. The defect detection methods employing texture features extracted from fractal dimension, first-order statistics, cross correlation, edge detection, morphological operations, co-occurrence matrix, eigenfilters, rank-order functions, and many local linear transforms have been categorized into this class. A brief introduction of each of these methods is now presented.

4.1.1 Defect detection using fractal dimension

Conci and Proença [45] have used the estimate of Fractal dimension (*FD*) on inspection images to detect fabric defects. In order to process large amount of image data, they have implemented the differential box counting method with the few modifications so as to minimize computational complexity and to enhance efficiency. The decision for defect declaration is based on the variation of *FD*. The defect detection approach investigated in [45] is computationally simple but presents very limited experimental results which suggest very limited but suggest 96% detection on eight types of defects. The localization accuracy of these detected defects is very poor and have high false alarm.

4.1.2 Defect detection using bi-level thresholding

One of the simplest methods to detect high contrast defects is to directly use gray level thresholding. The presence of high contrast defect causes the received signal to raise or fall momentarily, and the resultant peak or the trough can be detected by thresholding. Norton-Wayne *et al.* [46]-[47] have used this idea to detect fabric defects on the textile web moving at the speed of one meter per second. The random noise present in 1-D signal generates the false alarms in the form of isolated triggers. Therefore, authors have only accounted clustered triggers generated after thresholding. Bradshaw [48] and Cho *et al*. [165] have also detailed fabric defect detection using bi-level thresholding. Stojanovic [25] *et al*. have also developed a fabric inspection system that uses thresholding, noise removal followed by local averaging to identify eight category of defects with 86.2% accuracy, however with 4.3% of false alarm. Another related work that uses fast adaptive thresholding limit to detect low contrast defects in galvanized metallic strips appears in reference [49]. The advantage of defect detection techniques based on bi-level thresholding lies in its ease of implementation but such techniques fail to detect those defects which appear without altering mean gray level in defect-free areas.

4.1.3 Defect detection using gray level statistics

Independent classifications of image pixels, as used in reference [46], is likely to perform poorly since locally there may not be sufficient information to make good decision on the low contrast defects. Therefore, most defect detection algorithms impose some form of smoothness either implicitly or explicitly before the thresholding. Zhang and Bresee [50] have done this by dividing the inspection images into arbitrary blocks

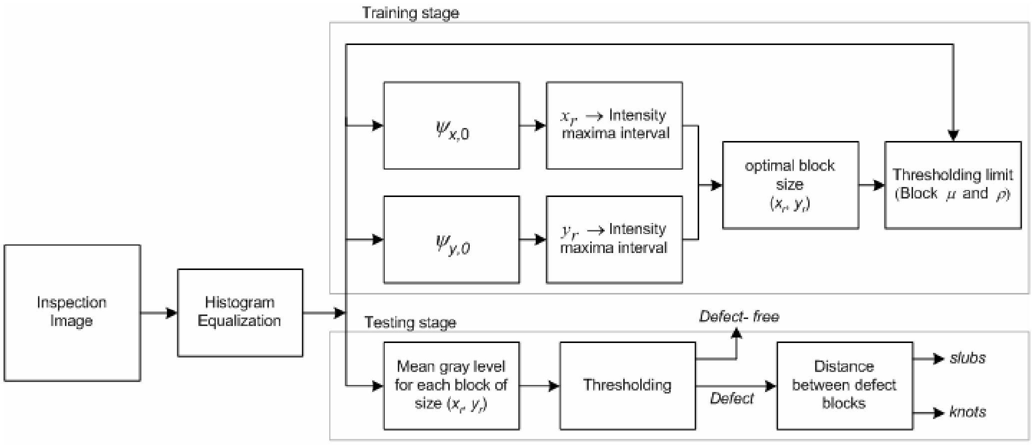

Figure 3 : Defect detection based on statistical block processing.

and classifying these blocks into defect or defect-free class using their first order gray level statistics. However, if the block size chosen is too small, discrimination among the similar defect-free textures may be difficult. Alternatively, if the block size is too large, then the local regions having defective texture may be lost. Also the large block size will generate inaccurate defect boundaries since there is no reason to believe that the actual defect boundaries occurred along the block boundaries. Therefore the authors [50] have used autocorrelation function ($\psi_{x,0}, \psi_{y,0}$), as shown in Fig. 3, to select the optimal block size.

Another scheme used by Hurt and Postaire [51] and is worth mentioning, uses threefold strategy to detect defects. The defects in the weft- and warp-directions are calculated separately using 1-D pixel data from the line-scan cameras. The defect detection from each of the two separate 1-D signals is achieved by thresholding, which is similar to as detailed in section 4.1.2. The thresholding limit is determined from the defect-free fabric, similar manner as in [50]. An important feature of this algorithm is the online monitoring. When a defect in the warp direction (usually long) begins, a short time later an alarm is generated to alert the operator so that he can take corrective action. Thomas and Cattoen [52] have used raised cosine filter to suppress high frequencies (harmonics) and retain the fundamental frequency corresponding to the periodicity of yarns. Bi-level thresholding on these filtered image sub-blocks has enabled reliable defect detection. Some fabric defects [26] can be easily identified by their color. Tsai and Tsai [4] have recently proposed the use of color ring-projection algorithm for computational ease and demonstrated the defect detection which is invariant to the texture rotation. Chetverikov [53] has introduced the quantitative definition of *maximal regularity*, and has shown it to be consistent with the human judgment [166] on regularity of textures. The *maximum regularity* is derived from the gray-level statistics (periodicity autocorrelation function) of textile image. The extensive set of results presented in [6], using *regularity* and *orientation* measures, are one of the best in the fabric defect detection literature. The method proposed in [50] fail to detect those fabric defects which appear by changing second and higher order moments, *e.g*. mispick, which have been successfully detected using the texture measures of regularity in [6]. The main advantage of approaches in [50]-[52] is their computational simplicity which makes them attractive for implementation using a simple general purpose computer. However the utility of method suggested in [6] for online fabric inspection is low as the execution time for 256 × 256 pixels image has been stated to be more than a minute, besides the method does not have any automated method of selecting thresholds.

4.1.4 Defect detection using morphological operations

Detection of fabric defects using morphological operations has been detailed in [50]. Every inspection image is histogram equalized and then thresholded to produce binary image. The binary image of a defect-free fabric (during training) is used to extract the optimal size and the shape of Structuring Element (*SE*) using autocorrelation function as detailed in section 4.1.3. This optimal size of *SE* is used during the testing phase. Every binary test image is subjected to erosion and then to dilation using this *SE*. The distance between the resulting defective pixels (if any) has been used to group defects into *slubs* or *knot* defects. The practical utility of this approach is limited as most of the commonly occurring fabric defects will be missing from the binary image generated from the simple thresholding operation.

Mallik-Goswami and Datta [54] have also detected fabric defects using laser-based morphological operations. This approach filters out the periodic structure of fabric in the optical domain by inserting Fouries lens after proper spatial filtering. Thus the morphological operations are only performed on aperiodic images defects, unlike the case in [50] where the entire structure of thresholded fabric image was utilized. However the experimental results presented in [54] are on obvious defects and do not suggest any advantage over other available less complex approaches.

4.1.5 Defect detection using edge detection

The distribution of the amount of edge per unit area is an important feature in the textured images. The amount of gray level transitions in the fabric image can represents lines, edges, point defects and other spatial discontinuities. These features have been used to detect fabric defects [55]-[57]. Conci and Proença [56] have used Sobel edge detection to detect fabric defects and compared the results with those based on thresholding and fractal dimension. However, they have not described their methodology and have only discussed their comparison. J. S. Lane [57] has detailed a systematic approach to detect fabric defect in a recent U.S. patent. The image under inspection is transformed into a gradient image using a set of masks. This gradient image is thresholded to separate possible defect pixels from the non-defect pixels. The resultant image is dilated with the *SE* to further segregate the defect pixels from the noise. The last step is the blob analysis, which labels the connected pixels as objects. Another useful approach for the characterization of low resolution web surface using facet model appears in [74]. The design and implementation of application specific integrated circuits (ASIC) for the edge detection based real-time defect detection has been detailed in [101]. The defect detection approaches [55]-[57], [74] using edge detection are suitable for plain weave fabrics imaged at low-resolution. The difficulty in isolating fabric defects with the noise generated from the fabric structure results in high false alarm rate and therefore makes them less attractive for textile inspection.

4.1.6 Defect detection using normalized cross-correlation

The cross-correlation function provides a direct and accurate measure of similarity between the two images. Any significant variation in the value of this measure indicates the presence of a defect. Bodnarova et al. [58] have used the correlation coefficient from multiple templates to generate a correlation map for defect declaration. One of the major problems with this method is its ad-hoc selection of template and window sizes. The experimental results presented in [58]-[59] are few and do not show any advantage over those based on first order statistical moments in [50]-[51].

4.1.7 Defect detection using co-occurrence matrix features

Texture is a neighborhood property therefore spatial interactions among neighboring pixels have been used for the characterization of textures. Siew et al. [61] presented the assessment of carpet wear using Spatial

Gray Level Dependence Matrix[2] (SGLDM), Gray Level Run Length Matrix (GLRLM), and Gray level Dependence Matrix (GLDM) [60]. The gray level co-occurrence matrix is one of the most popular statistical texture analysis tools and has also been used for the detection of surface defects on wood [62] and fabrics [63*]. The classical approaches based on the estimation of statistical moments (e.g. mean and variance [46]-[52]) or some other statistical parameters (AR [?]) allow very quick characterization of fabric images. On the other hand the methods based on higher order statistics (e.g. co-occurrence matrix [62]-[64], [66], [68], GLRLM, GLDM) provide more information but are computationally more demanding in terms of both computational and memory requirements.*

Harlick *et al.* [65] have derived 14 features from the co-occurrence matrix and used them successfully for characterization of textures such as grass, wood, corn, *etc*.. However only six of such features have been used for the defect detection on wood, and fabric defect detection has been shown with only two [63] (four [64]) of these six features. Conners *et al*. [62] have used six features of the co-occurrence matrix, to identify nine different kinds of surface defects in wood. Tsai *et al*. [63] have detailed fabric defect detection while using only two feature, *i.e*. ASM and CON, and achieved classification rate as high as 96%. Rösler [66] has also developed a real fabric defect detection system, using co-occurrence matrix features, which can detect 95 % of the defects as small as 1 mm^2 in size. In order to derive maximum texture information using co-occurrence matrix, the values of parameter θ should agree with the orientation of the fabric pattern and the distance d should be equal to the pattern period [67]. Bodnarova *et al*. [68] have examined this issue on the optimal displacement vector $\boldsymbol{d}$ for the fabric defect detection. The five elemental feature matrices (EFMs) [69], corresponding to the five features [70], is derived and subjected to a χ^2 significance test for defect declaration. Another related approach to detect magnetic disk defects using co-occurrence spectrum of 4th order rank appears in [71]. There are two major problems in the conventional use of co-occurrence matrix in fabric defect detection, inefficient portioning of co-occurrence space and inefficient description of multipixel co-occurrence, which should be addressed to achieve the best possible performance for online fabric

[2] SGLDM is frequently referred to as gray level co-occurrence matrix.

inspection. Also, the asymmetric co-occurrence matrix contains more information about texture orientation and than therefore should be preferred than the symmetrical ones.

4.1.8 Defect detection using eigenfilters

The information content of defect-free fabric image can also be extracted by registering the variations in an ensamble of macro windows within the image, independent of any judgment of its texture. Unser and Ade [72]-[73] use this local information to construct eigenfilters for defect detection in textured materials. Monadjemi [161]-[162] has suggested the usage of structurally matched eigenfilters, which are generated by rotation, negation and mirroring, for textured defect detection. Another approach with limited results that uses eigenvalues as feature vector and Neyman-Pearson test for defect declaration is described in [136]. The eigenfilter based approaches are useful in separating pairwise linear dependencies, rather than higher-order dependencies, between image pixels. The important information in most fabric textures is contained in higher order relationships among image pixels. Therefore fabric defect detection using Independent Component Analysis (ICA) of fabric texture has been suggested in [160]. However, these appearance based approaches using eigenfilters or ICA are highly sensitive to local fabric distortions and background noise, and are therefore not attractive for online fabric inspection.

4.1.9 Defect detection using local linear transforms

Several popular bi-dimensional transforms such as Discrete Cosine Transform (DCT), Discrete Sine Transform (DST) or Discrete Hadamard Transform (DHT) can be used for the extraction of local texture properties. Ade *et al.* [75] have compared the performance of the several local linear transforms, *i.e*. DCT, DST, DHT, eigenfilters, and Laws masks for the fabric defect detection. Their approach is similar to the one discussed in Sec. 4.1.8, when 3×3 and 5×5 DCT, DST, DHT, and Laws masks are (separately) substituted for eigenfilters. Hadamard transform is primarily defined for sizes, which are multiple of four. Therefore pseudo-Hadamard transform has been used to obtain 3×3 and 5×5 masks by truncation of proper Hadamard masks of required size. The results of their experiments [75] have compared favorably with the set of empirical filters introduced by Laws. However their dataset was limited to only two types of fabric defects and therefore their results are subjective and lack generality. Neubauer [76] has detected fabric defects using texture energy features derived from the Laws masks on 10 × 10 windows of inspection images. In his approach, three 5 × 5 Laws masks corresponding to ripple, edge, and weave features [77] are used to extract histogram features from the every window of the image. These features are then used for the classification of corresponding window into defect-free of defect class, using a three layer neural network.

Őzdemir and Erçil [78] have implemented fabric defect detection using an approach which is a variation of the Karhunen-Loève (KL) transform or eigenfilters method described in Sec. 4.1.8. Instead of using the eigenvectors of the covariance matrix, they have used the eigenvalues of covariance matrix as a feature and justified it on the basis of computational savings. The sum of the largest three eigenvalues of this covariance matrix is taken as a feature for each of the sub-windows [79]. In online fabric inspection, the local transforms such as DCT or DST could be preferable to the eigenfilters or KL transforms, since DCT or DST can be directly obtained from the camera hardware using commercially available chips that perform fast and efficient DCT or DST transforms.

4.1.10 Defect detection using rank-order functions

The rank-function of a given image is derived from its histogram, and is given by the sequence of gray levels in the histogram when the sequence is sorted in the ascending order [81]. There exists 1:1 correspondence between the rank function and the related histogram, which does not exist between histogram and the image[3]. Therefore the histogram and the rank function provide exactly the same information. However, the advantage of using rank functions instead of histograms lies in the fact that there exists very efficient definition of rank-distances that can be efficiently computed. Natale [80] has used rank order functions for the detection of artificially introduced defects in some Brodatz textures [82]. He introduced appropriate rank-distance functions, which proved to have substantial advantage over the classical histogram based approaches for the defect detection. Another related work for the parquet slab grading using cumulative histogram is described in [7]. Desoli *et al.* [81] have shown the defect detection in ceramic tiles using a set of adaptive rank order functions. The color information in textured images can also be used to extract color histograms and this has been used in references [83]-[84] to detect defects. The fabric texture information regarding spatial

[3] Many different images may share the same histogram.

distribution and orientation, etc., is not uniquely determined from the knowledge of rank order functions. Due to such drawbacks the approaches rank order functions or classical histogram analysis have failed to generate any further interest for fabric defect detection.

4.1.11 Defect detection using neural-networks

Neural networks are among the best classifiers used for fault detection due to their non-parametric nature and ability to describe complex decision regions. The problem of fabric defect segmentation using feed-forward neural networks (FFN) has been investigated in [5]. A low-cost solution for fabric defect detection using linear neural networks has also been detailed in [1], [5]. Recently, Hung and Chen [8] have used the back-propagation neural network, with the fuzzification technique (fuzzy logic), to achieve the classification of eight different kinds of fabric defects along with the defect-free fabric. A compact fabric inspection system using neural network is described in [11] but is not adequately detailed. A framework for real time visual inspection using the self-organizing map based classifier with a log-likelihood dissimilarity measure is presented in [9]. The Support Vector Machines (SVM) offer attractive alternative to FFN as they do not suffer from the problem of local minimum and are computationally simpler to train. Therefore fabric defect detection using SVM has been proposed in [141]. Another related work for the texture defect detection using cellular neural networks appears in [12]. The FFN and SVM require training from the known classes of fabric defects. A large number of fabric defect classes with large intra-class diversity remain major obstacles in using FFN [5], [11] and SVM [141] based approaches for online fabric inspection.

4.2 Spectral approaches

Many common low-level statistical approaches such as edge detection break down for several fabric defects that appear as subtle intensity transitions. It is therefore critical to explore other robust and efficient computer vision approaches for fabric defect detection. Uniform textured images are composed of repetition of some basic texture primitives with a deterministic rule of displacement. The high degree of periodicity of basic texture primitives, such as yarns in case of textile fabric, permits the usage of spectral features for the detection of defects. However random textured images cannot be described in terms of primitives and displacement rules as the distribution of gray levels in such images is rather stochastic. Therefore spectral approaches are not suitable for the detection of defects in random textured materials. Early work on the assessment of carpet wear [61] has suggested that it may be possible to find spatial-frequency domain features which are less sensitive to noise and intensity variations than those features extracted from spatial domain. The psychophysical research has also indicated that human visual system analyzes the textured images in spatial-frequency domain. Several applications of frequency and spatial-frequency domain features for the detection of defects in uniform textured materials have been reported in the literature. The spectral approaches occupy largest volume of references for fabric defect detection and summarized in the following sections.

4.2.1 Defect detection using discrete Fourier transform

The Fourier transform has the desirable properties of noise immunity, translation invariance and the optimal characterization of periodic features. The woven fabric image is a combination of warp and weft yarn patterns. Each of these yarns is effectively 1-D and may be modeled by a comb of impulses that are modulated by the profile of one yarn [85]. Due to the stochastic textured components on the real fabric images, the local maxima peaks in the 2-D frequency plane are not properly localized. Therefore Sari-Sarraf and Goddard [86] have used perfectly contiguous and non-overlapping concentric rings of constant width to include various amount of loosely localized frequency components. The authors [86] have used the local statistics of these 1-D signatures to monitor yarn densities, rather than defects, of woven fabrics. However, Chan and Pang [87] have detailed the usage of localized frequency components for the identification of real fabric defects. Tsai and Hu [88] have presented Fourier models of four different kinds of fabric defects; *missing end*, *missing pick*, *broken fabric* and *oily fabric*. They have used these models to extract Fourier features of the real fabric defects using DFT.

Tsai and Heish [89] have detected defects in the directional textures, such as fabrics and machined surfaces, using a combination of DFT and Hough transform [163]. The DFT of gray-level images of such textures shows the high-energy frequency components which are detected by 1-D Hough transform. As shown in Fig. 4, after suppressing specific regions in the Fourier domain images, inverse DFT (IDFT) is used to recover the images

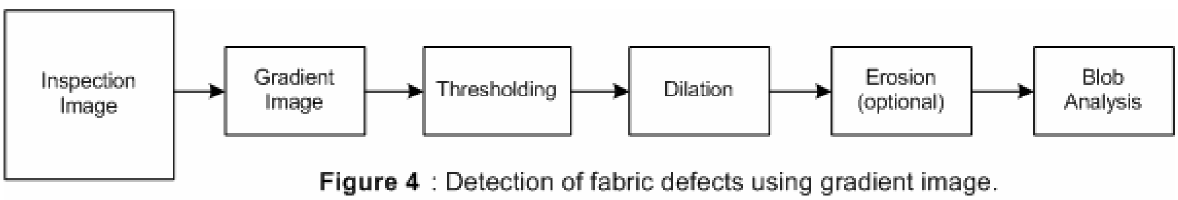

Figure 4 : Detection of fabric defects using gradient image.

in the spatial domain. Thus, IDFT preserves only local anomalies (defects) if they appear on the original gray-level images, and removes all the homogenous and directional textures of the original images. The DFT based approaches are not effective in those fabric images in which the frequency components associated with the homogenous and defective images are highly mixed together in Fourier domain. It is due to the difficulty in manipulating the frequency components associated with homogenous regions without affecting the corresponding components associated with the defective regions.

4.2.2 Defect detection using optical Fourier transform

The Fourier transform of textile fabrics can also be obtained in optical domain by using lenses and spatial filters. Therefore, the detection of fabric defects using optical Fourier transform (OFT) is relatively easy and fast. The Fraunhoffer diffraction pattern of an object (fabric) is the Fourier transform of that object [90]. The luminous intensities of the zero- and the first-order diffraction patterns are modulated by the existence of fabric defects [91]. Therefore the fabric defect detection systems using the measurements of the first- and the zero-order intensities have been developed [92]-[95]. Ciamberlini *et al*. [96] have described the design of spatial filters, both a fixed filter adaptable for different types of fabric and a universal spatial filter, for the detection of defects in the textured materials. Similarly, Kim *et al*. [97] have used pinhole type spatial filters on the OFT images to detect shadow mask defects of size as small as 500 μm^2.

The diameter of laser beam employed to generate OFT image of the moving fabric cannot be too large relative the spacing of weft and warp yarns in the fabric. The small beam diameter requires multiple optical systems [99] to cover the width of fabric, which is very costly and complex. Therefore, Fomenko [98] has used high-speed swinging, scanning and de-scanning, mirrors to scan across the width of the fabric from one edge to another. The OFT images are not only useful for the detection of fabric defects but also for their classification. Hoffer *et al*. [100] have used a small subset of pixels from the OFT images to classify fabric defects into four categories using a three-layer 64/20/5 back-propagation neural network.

4.2.3 Defect detection using windowed Fourier transform

Defect detection methods based on DFT and OFT are inadequate when the location of defects, *i.e.* spatial localization is desired. Furthermore, the small or the local defects may be swamped in the inevitable averaging that takes place in the feature estimation of large image regions. *Thus the DFT and OFT based techniques are suitable for global defects rather than local defects*. Detection of local defects requires the techniques that can localize and analyze the features in spatial as well as frequency domain. Therefore features based on space-dependent Fourier transform *or* running-window Fourier transform *or* windowed Fourier transform have been suggested for the fabric defect detection. Campbell and Murtagh [102] have detailed a WFT based method to detect defects on *denim* fabric samples. A 16 × 16 pixels window is used to extract amplitude spectrum features using WFT. Similar features are extracted from a defect-free fabric sample and defects are detected using a hypothesis test based on Neyman-Pearson criterion [103]-[104]. Campbell *et al*. [105] have shown that the feature extraction using WFT and the subsequent decision mechanism has the potential for parallel implementation via a feed-forward neural network structure. They have computed WFT features in 32 × 32 pixels moving windows to detect *denim* fabric defects.

4.2.4 Defect detection using Gabor filters

The effectiveness of WFT based approaches has illustrated the importance of the conjoint analysis of the textured images in both spatial and frequency domains. Consequently, the texture features that represent the frequency content in localized regions in the spatial domain have attracted the attention of many researchers. These features can be extracted from the inspection images by the localized spatial filtering. The 2-D Gabor filters are appropriate for this spatial filtering in many senses [106]: they have tunable angular and axial frequency bandwidths, tunable center frequencies, and achieve optimal joint resolution in spatial and frequency domain. The parameters of a Gabor filter can be selectively optimized to discriminate a known category of defects. Such segmentation of fabric defects using best or optimal Gabor filter has been demonstrated in [17], [109]-[111], [143]. The dimension and orientation of local defects generated on the textile web varies randomly. Therefore a general web inspection system using a bank of symmetric and asymmetric Gabors filters has been detailed in [107]-[108], [156] and [143] respectively. Real part of Gabor filter has been shown to act as a blob detector. The mechanism of texture segmentation in human visual system has been described with the Real Gabor Functions (RGFs) and the sigmoidal shaped nonlinearity in the retinal adaptions. Therefore a bank of multiorientation and multiresolution RGF, followed by intra- and inter-scale image fusion (Fig. 5), has suggested to segment fabric defects [14], [158]. Kumar [1], [23] has also demonstrated that the dominant spectral component in defect-free fabric can be computed from the FFT decomposition and used to automatically select the center frequencies of Gabor filters.

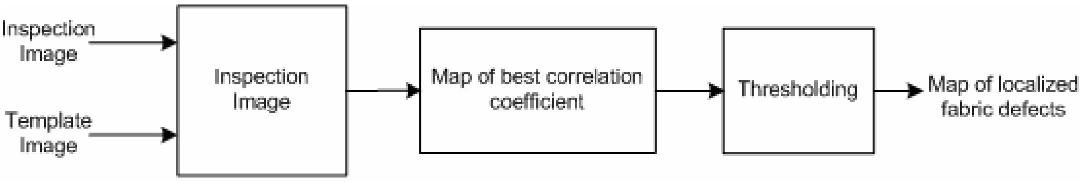

Figure 5 : Fabric defect detection using Cross-correlation function.

4.2.5 Defect detection using Optimized FIR filters

Some fabric defects that produce very subtle intensity transitions may be difficult to detect using above spectral approaches. A potential solution to the detection of such defects is to employ optimal finite impulse response (FIR) filters. The optimization offers the potential of large feature separation between the defect-free and the defective regions of the filtered image. The Gabor filters and the infinite impulse response (IIR) filters are the filters with only a few free parameters and therefore the search space for optimization is very restricted. Better optimization results can be obtained when the number of free available parameters of a filter is large. A general FIR filter has generally more free parameters than an IIR or a Gabor filter and thus offers added advantage of computational ease. The optimal FIR filters used for fabric defect detection in [18], [34] show high detection of very subtle defects and unsupervised inspection using a bank of these filters. Kumar [1], [34] has emphasized on smaller spatial masks, as compared to those from optimal Gabor filters, and demonstrated fabric defect segmentation with optimal FIR filters as small as 3×3 or 5×5 mask size.

4.2.6 Defect detection using Wigner distributions

The Wigner distribution function is Fourier-like but has been shown to offer better cojoint resolution than Gabor or difference of Gaussians for cojoint spatial and spatial-frequency image representation. Song *et al.* [19] have used a computational approximation to the Wigner distribution, *i.e.* pseudo-Wigner distribution, to demonstrate the detection of cracks in complex background textured materials. The proposed method has shown to be quite accurate and can also be used to effectively detect fabric defects. However the computation time for this algorithm is stated to be about two minute to inspect 256 × 256 pixels image which is prohibitive for its usage in real-time textile web inspection. The fabric defect detection approaches using optimal FIR filters and Wigner distributions have been shown to be quite effective to detect a class of fabric defects. However their utility for unsupervised web inspection, in simultaneously detecting defects from a large number of classes, is yet to be demonstrated.

4.2.7 Defect detection using Wavelet transform

The major drawback with the Wigner distributions is the presence of interference terms between the different components of an image [1]. Multiresolution decomposition using a bank of Gabor filters results is redundant features at different scales. This is due to the nonorthogonality of Gabor functions for which they are often criticized. The multiresolution decomposition using orthogonal (or biorthogonal) and compactly supported wavelet bases can be used to avoid the correlation of features between the scales. The multiscale wavelet representation posses the property of shift invariance and can be used for fabric defect detection by examining fabric images at different scales. Recently, Sari-Sarraf and Goddard [112] have developed a fabric defect detection system that can detect defects as small as 0.2 inches with an overall detection rate of 89 %. Their defect detection scheme uses the low-pass and the high-pass 'Daubechies' D2 filters [85]. The authors [112], [114] have shown that the two fractal-based measurements, local roughness $R(m,n)$ and global homogeneity GH, can be used to quantify surface characteristics of the real fabric images (Fig. 6). However the selection of wavelet scales in [112] [114] is limited due to their dyadic nature and can pose problem in the accurate localization of defects. Therefore multiscale representation of fabric image using B-spline transform is proposed [142] for defect detection.

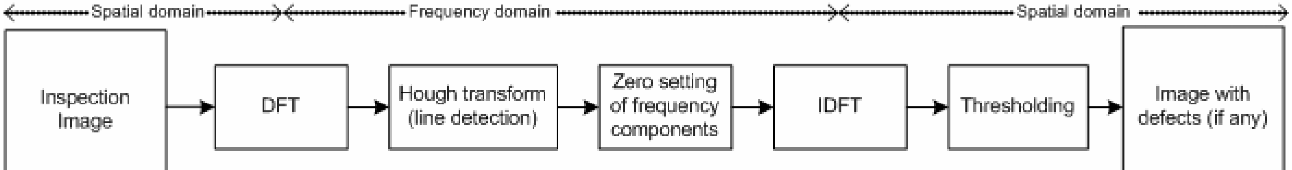

Figure 7 : Detection of fabric defects using DFT.

Kim *et al.* [115] have described a fabric defect detection scheme using wavelet analysis on 1-D projection signals. The two 1-D signals from every inspection images are generated by the gray-level summation of the pixels along the rows and columns respectively. The Mexican hat wavelets at the three scales are used to decompose each of these 1-D signals. The wavelet coefficients of each of these three decomposed signals are used to compute the respective signal to noise ratio (SNR) and then declare the defects. A simplified version of this algorithm to detect the fabric defects from low-resolution inspection images has been detailed in [40].

The 1-D signals used by Kim *et al*. [115] do not preserve the adjacency of features, except in the two directions of scanning. Therefore, 1-D signals generated from the inspection images using the fractal scanning have been used for the fabric defect detection [155]. The fractal scanning technique uses inherent scaling and nesting properties of fractals, which can preserve the neighborhood relationship of 2-D image data. Recently, a system developed at the Georgia Institute of Technology, for the fabric defect detection and identification, details [116]-[120] the usage of a fuzzy wavelet analysis technique employing fractal scanning. This approach generates the wavelet coefficients across the several scales are then nonlinearly combines them by a fuzzy inference mechanism. The decision on the defect declaration and identification is made by comparing these fuzzified features with the templates stored in the knowledge-base. Using this decision mechanism, the authors [116]-[120] have classified the fabric defects primarily into three categories: line, point and area defects. The conventional wavelet transform decomposes the image in the low frequency regions but the most significant/dominant information in fabric texture often lies in the middle frequency bands. Therefore the location of significant frequency bands and their decomposition using wavelet packets have been suggested [137] to identify fabric defects.

Jasper *et al*. [121], [159] have detailed the design of a texture specific wavelet basis filter, which can be tuned to a particular texture. Similar work on the design of adaptive wavelet bases but with the nonsubsampled wavelet transform appears in [39], [124]. The design of such adaptive orthonormal wavelet bases has also been shown [127] to achieve the best performance in the characterization of fabric defects. The wavelet coefficients can also be selectively used to reconstruct the fabric image which is lacking in texture so as to enhance the defects which can be later segmented by thresholding. Such an approach is detailed in [24] however with limited experimental results. Lambert and Bock [122] have used four-scale dyadic wavelet decomposition to extract features from the textured images. These features are then used with a neural net classifier to detect defects in the textured image. The detection of fabric defects using wavelet packet decomposition and independent component analysis has been investigated in [164]. Kumar and Gupta [123] have used mean and variance of 'Haar' wavelet coefficients for the identification of surface defects. The fabric texture can also be considered as noise and removed using wavelet shrinkage. However, such approach [113], [134] cannot detect defects that appear as subtle change in fabric texture.

4.3 Model-based approaches

Texture is usually regarded as a complex pictorial pattern and can be defined by a stochastic or a deterministic model. However, the real textures, such as fabrics, are often mixed with stochastic and deterministic components. The real textures can be modeled as stochastic process, and textured images can be observed as the realizations or the samples from parametric probability distributions on the image space [125]. The advantage of this modeling is that it can produce textures that can match the observed textures. The defect detection problem can be treated as a statistical hypothesis-testing problem on the statistics derived from this model. Model-based approaches are particularly suitable for fabric images with stochastic surface variations (possibly due to fiber heap or noise) or for randomly textured fabrics for which the statistical and spectral approaches have not yet shown their utility. Several probabilistic models of the textures have been proposed and used for the defect detection. These model-based methods for defect detection are now briefly discussed.

4.3.1 Defect detection using Gauss Markov Random Field model

The stochastic models based on the Gauss Markov Random Field (GMRF) have been successfully shown to model many natural and man-made textures [126]. Cohen *et al*. [157] have detailed the fabric defect detection using the GMRF model. The defect-free fabric is modeled by GMRF, whose parameters are estimated from the training samples observed at a given orientation and scale. Authors classify each of the textile blocks into defective or defect-free class using χ^2 test on maximum likelihood estimate (MLE) of the GMRF model parameters obtained from defect-free fabric. Fabric defect detection results using a similar approach have also been shown in [78], [125], and [128]. Őzdemir and Erçil [78], Baykut *et al*. [135] have implemented GMRF based fabric defect detection scheme on a TMS320C40 based system. They have shown that the fifth-order

GMRF based defect detection scheme runs at about 10 times faster than that based on KL transform (section 4.1.8). Attali and Cohen [129] have discussed stochastic modeling of textured images using Markov random field (MRF) and fractal models. They have suggested that the MRF based models are useful for modeling fabric textures while fractal models are suitable for modeling perceptual surface roughness.

4.3.2 Defect detection using Poisson's model

The stochastic models of some of the randomly textured materials that are produced in the industry are based on the nature of the manufacturing process. One example of such material is the fibrous, nonwoven material obtained by malt blowing polypropylene resin and used for air filtration. Brzaković *et al*. [21], [130] have investigated the problem of defect detection in such randomly textured surfaces. Authors in reference [130] have shown that the difference between the theoretical model prediction (estimated) and actual measurements from the defect-free images is within 10 %. Thus a statistical hypothesis testing between these two measurements can also be used to detect the fabric defects.

4.3.3 Defect detection using model-based clustering

The problem of locating possible clusters in a data set (image) is a recurrent one with a long history. Campbell *et al*. [131] have used model-based clustering to detect relatively faint aligned defects in the *denim* fabrics. In order to assess the evidence for the presence of a defect, Bayesian information criterion (BIC) [132] is used. The authors in reference [131] have used a chain of pre-processing operations, *i.e.* thresholding, opening, labeling, object centroiding, before the estimation of BIC from the inspection images. The results from this work suggest that the BIC value is invariably a reliable indicator for the presence of defects. Kong *et al*. [133] have used a new color- clustering scheme for the detection of defects on the colored random textured images. This new scheme uses initial clustering involving K-mean clustering and a perceptual merging. As detailed in reference [133], the performance of this algorithm is excellent for all color images. However the performance is not satisfactory if the image is dominated by gray colors.

5. Discussion

Quality assurance of textile materials using automated visual inspection depends on the range of defects that can be detected by the employed defect detection method. In order to detect the defects with subtle intensity variations, they have to be imaged with sufficient resolutions so that their details are visible in the texture background. Resolution of the acquired images is an important factor in selecting the suitability of an approach for the defect detection. A quantitative comparison between the various defect detection schemes surveyed in this paper is difficult as the performance of each of these schemes have been assessed/reported on the fabric test images with varying resolution, background texture and defects. Higher computational complexity can be justified with better performance on high resolution images but this also may not always hold good in various applications and overall cost of system. Therefore comments/conclusions on the suitability of some approaches, recently cited in the literature, based on the image resolution, computational complexity, and performance would be useful. The approaches developed in [5], [18], [23], [143] have been in evaluated on image sample with either of these resolutions (approximate); (i) 50 pixels per inch (PPI) [5] [143], (ii) 100 PPI [14] [23], and (iii) 200 PPI [18] [5]. Low-resolution images of the order of 50 PPI are accompanied by distortion due to the geometry of the imaging lens and/or non-uniform illumination [1]. Therefore, approaches described in the literature using RGFs, Gabor filters, FFN or wavelet packets may not be suitable for such images. Instead, inspection methods using imaginary Gabor functions (IGFs) [143] and linear neural networks [5] have been aptly developed for such low-resolution images. A comparative evaluation of these two approaches along with other edge-detection methods [144] can determine the final choice for the inspection of textile webs using such low-resolution images.

Images with 100 PPI of resolution [14] have also shown some distortions. This distortion has been corrected to some extent by the equalization of acquired images. Unsupervised web inspection using RGFs [14], [23] can be a good choice for online inspection images of this medium resolution, and is hence suggested. This suggestion is based on the two factors: (i) this method has shown a high degree of robustness for the detection of variety of defects, (ii) the resolution of images used to show the experimental results offers a good compromise between the computational complexity and the performance, *i.e.* high resolution images will demand more online computations for the entire web inspection and low-resolution images will not capture some of the defects with subtle intensity variation (and therefore they cannot be detected).

High-resolution images with 200 PPI have been used to show the experimental results from the defect detection method using optimal FIR filters. The defect segmentation method using FFN [5] or SVM [141] are expected to perform poorly on low-resolution images (50 PPI) as it is highly sensitive to image distortions. The defect detection method using wavelet packet will also loose its relevance in such images, *i.e*. if the details of those defects that are embedded in the texture are not visible. The high-resolution images are highly suitable for detecting defects with very subtle intensity variations, but their use will require a high volume of online computations for unsupervised defect detection. However, supervised defect detection on these high-resolution images is a real possibility and is therefore suggested for its practical usage. Since the FIR filters have more free parameters than a Gabor filter, the size of optimized FIR filter masks are expected to be smaller than those for optimal Gabor filters. Therefore, optimized FIR filters should be preferred over the optimal Gabor filters [17] for supervised defect detection. In situations where the computational requirements is not a limitation, then the unsupervised web inspection method using a large number of asymmetric Gabor filters (AGF), on high-resolution web images can be the judicious choice among methods in Table 1. To sum up, the selection of a defect detection approach largely depends on the available computational power for online inspection. Fig. 1 illustrated [1] examples of typical fabric defects acquired with different imaging resolutions. Table 1 presents a summary on the effect of resolution for the proposed methods. This table also depicts a rough estimate on the employed computational complexity *i.e*. operations per pixel used for these methods. The conclusions/suggestions are largely based on the experimental results illustrated in the cited literature.

Baykut *et al*. [135] have concluded that the MRF (9^{th} order with 25 sufficient statistics) performs better than Laws mask, eigenfilter, lattice filter and FFT based approaches on images of about 100 PPI resolution. Similarly, Bodnarova *et al*. [17] have concluded that the optimal Gabor filters (optimized to detect five types of defects) perform better than gray level co-occurrence matrix, correlation or FFT based approaches. However this comparison is very limited on a set of 25 images and the information about the

Table 1: Summary on image resolution and operations per pixel for the proposed methods.

Method / PPI	RGF [14], [23]	IGF [143]	AGF [143]	OF [18]	NN-1 [5]	NN-2 [5]	MRF [135]
50	√	√	√	NA	√(bad)	√	NA
100	√	X	√	√	√(bad)	X	√
200	√	X	√	√	√	X	NA
Operations per pixel (appox.)	49 × n (n = 16)	2	81×2× n (n = 18)	170 × n (n = 2)	285	2	7

PPI: Pixels Per Inch, n: number of channels or filters.

image resolution is also missing. The comparisons in [135] and [17] did not include RGFs in [14] and Optimal FIR filters in [18] respectively, possibly due to the fact that these approaches were proposed in the literature published later. The recent texture inspection approach by Chetverikov and Henbury [6] using the measure of structural regularity and texture anisotropy is computationally expensive and requires much tuning. However the rigorous experimental results on Brodatz [82] and TILDAS [147] dataset are quite convincing and suggest that these two measures can compliment each other. Therefore a combination of these

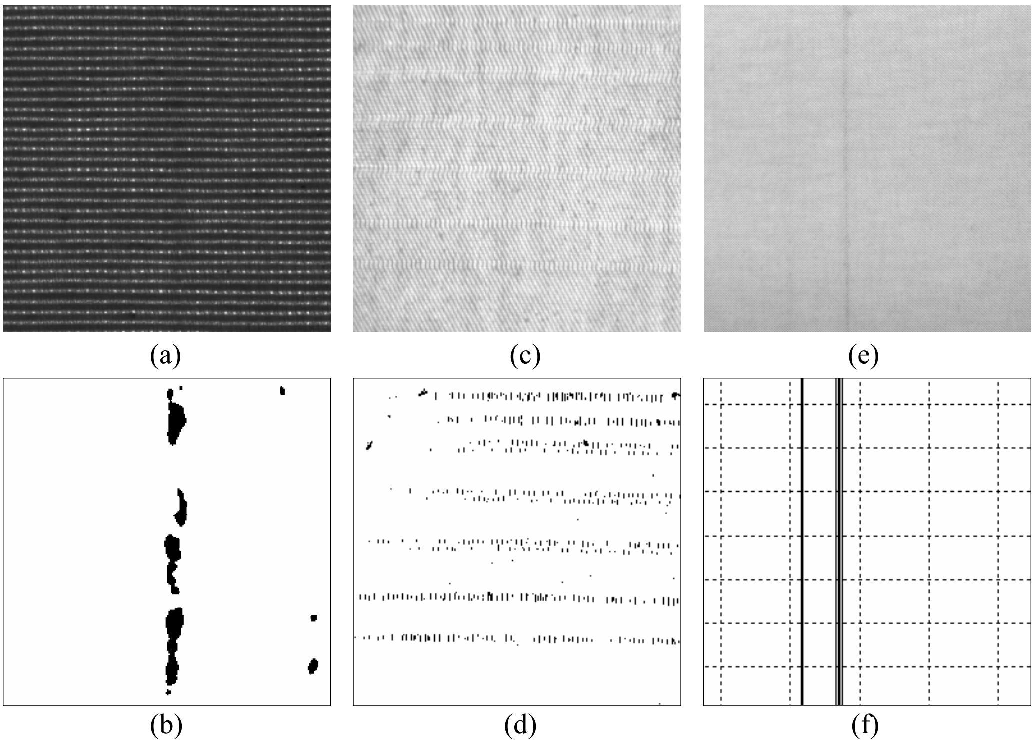

Figure 7: Typical fabric image sample acquired at about (a) 200 PPI with defect *tripe-warp* (b), 100 PPI with defect *mispick*, and (c) 50 PPI with *slack-end*; corresponding detected defects can be seen in (b), (d) and (f)

two approaches can offer the best performance for textile web inspection and is suggested for further investigation and comparison. Another aspect of textile web inspection problem deals with the inspection of patterned webs and has remained largely unexplored. Most of the earlier attempts [140], [148-153] to this problem have focused on mechatronics approach, *i.e.* alignment of patterns by controlling/tracing the movement of textile web and then using image subtraction. The detection of genuine defects and separation of false alarms is achieved from the subtracted image [148]. This problem requires the renewed attention using purely computer vision approach, *i.e.* automated location of patterns using machine vision and detection of defects when the patterns are arbitrarily rotated and/or partially occluded.

6. Conclusions

This paper has provided a survey of fabric defect detection methodologies reported in about 150 references. These available techniques were classified into three categories: statistical, spectral and model-based. The core ideas of these methodologies along with their drawbacks/critics were discussed whenever known. However, due to the lack of uniformity in the image dataset, performance evaluation and the nature of intended application, it is not prudent to explicitly declare the best available methods. Therefore Sec. 5 in this paper has attempted to classify some of the proposed methods using the approximate resolution of employed images, *i.e.* low, medium and high, and their computational complexity. The selection of image resolution, for the textile web inspection, is largely determined from the available computational power and expected performance. High-resolution inspection images will require more computing power to inspect entire width of web but are desirable to detect subtle defects. On the other hand, computational requirements are low for the low-resolution images but these images cannot be expected to detect subtle defects that are lost due to the low-resolution imaging. Some of the related work on the inspection of textile web, *i.e.* yarns spacing, winkle detection, pilling evaluation, design evaluation, defect classification *etc*., has been largely excluded from this paper. There has not been any prior survey on the fabric defect detection methodologies and the comprehensive survey (up to the second half of 2004) presented in this paper will be useful in developing and analyzing new approaches.

The last few years have shown some encouraging trends in fabric defect detection research. However, the researchers need to more seriously consider systematic/comparative performance evaluation based on realistic assumptions. The effective performance evaluation requires careful selection of data sets along with its clear definition of scope. This will remove any subjective judgment of results and allow the users to know which algorithms are competitive in which domain. Despite the significant progress in last decade, the problem of fabric defect detection still remains challenging and requires further attention. The statistical, spectral and model-based approaches give different results and therefore the combination of these approaches can give better results, than either one individually, and is suggested for future research.

7. Acknowledgements

The author would like to thank the anonymous reviewers for their valuable comments and suggestions.

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