Computer-Vision-Based Fabric Defect Detection: A Survey

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***Abstract*—The investment in an automated fabric defect detection system is more than economical when reduction in labor cost and associated benefits are considered. The development of a 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 the 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 any single approach, and is suggested for further research.**

***Index Terms*—Automated visual inspection (AVI), fabric defect detection, industrial inspection, quality assurance, textile inspection.**

I. Introduction

INEFFICIENCIES in industrial processes are costly in terms of time, money and consumer satisfaction. The global economic pressures have gradually led businesses to ask more of itself in order to become more competitive. As a result, intelligent visual inspection systems to ensure the 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 the visual inspection of these materials. As shown in Fig. 1, the automation problems for web inspection falls into two general categories based on the types of web materials [21]. The first category is 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 is 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, and wallpaper) requires the evaluation of color uniformity [149] and consistency of printed patterns, in addition to any discrepancy in the background texture. However, this has attracted little attention from 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 the weaving process involved.

A. 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 American Society for Testing and Materials D2255-96 [27], for predicting the quality of the 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

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

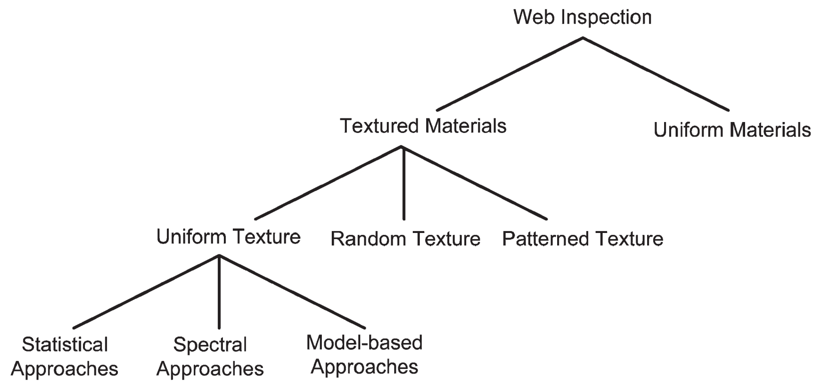

Fig. 1. Classification of a web inspection problem based on the nature of the surface.

and may not register recurring fabric defects that are generated due to sinusoidaly occurring inconsistencies 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 independent of yarn quality. The population of fabric defects may vary dynamically as small changes in the weaving process can result in an entirely new class of fabric defects.

B. *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 weaving machines is about 1.5–2 m wide, and rolls out at the speed of 0.3–0.5 m/min. Product inspection in the textile industries is not performed concurrently with production. The slow speed of the 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 m/min. 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.

II. Automation for Inspection

The automation of the visual inspection process [2] is a multifaceted problem and requires complex interaction among various system components. Nickolay and Schmalfuâ [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 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. Batchelor [30] has performed a comprehensive study of various lighting schemes for automated visual inspection (AVI). There are four common types of lighting schemes used for visual inspection, i.e., front, back, fiber-optic, and structured. Backlighting eliminates the shadow and glare effects, and is used for fabric inspection. It is also possible to employ fiber-optic illumination for 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 ft wide textile webs. A fuzzy logic control scheme using a feedback photoresistor is sometimes used by the illumination controller to maintain a constant (within 1%) level of illumination [31].

1) **Camera**: A large variety of cameras with tremendous difference in sensor types, resolution, readout 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

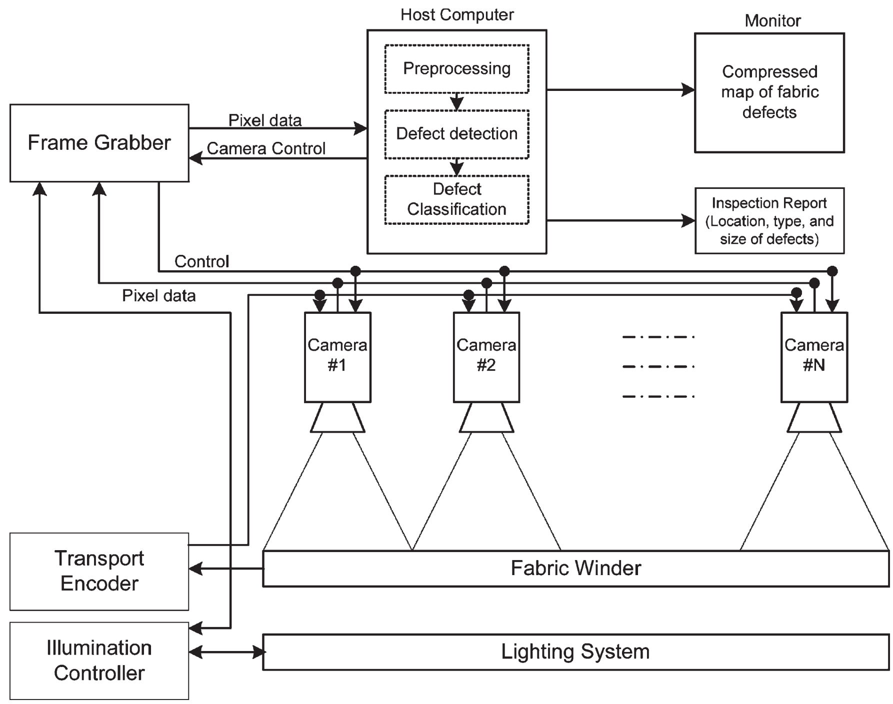

Fig. 2. Architecture of a typical textile web inspection system.

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 the object (web) movement and the scan rate (line rate) at which the camera is operating. Modern line scan cameras usually provide very high resolutions and can inspect a large portion of textile web in a 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 a complete image at once and requires an 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 the object (web) speed. Currently, 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 charge-coupled device (CCD) or CMOS photosensors. The photosensors with CMOS active pixel architecture provide a higher level of on-chip functionality at a 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 line scan cameras [31], [36] have been attempted by researchers.

2) **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 the 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 the shaft rollers [35].
3) **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 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.).
4) **Host computer**: The functions of the host computer can be classified into three main categories. 1) 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. 2) Camera illumination and control: The host computer is responsible for the external loading of the control setting parameters of the camera. These parameters are usually loaded at the power-up or operated manually through a Graphical User Interface (GUI). The host computer is

also responsible for the settings of the illumination controller, which controls the illumination level of the web. 3) System control: The host computer also performs several input and output system control functions. The functions in this category include Interrupt Service Routine, GUI and printing/storage of the compressed defect map, etc.

A single general purpose host computer is insufficient for processing a high volume of image data acquired to inspect the textile web moving at the speed of 15–20 m/min. 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 a real-time implementation of the 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, the large number of defect classes, interclass similarity and intraclass diversity of fabric defects form major obstacles in their classification.

III. Prior Literature Review

There have been four surveys of the 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 our knowledge, there has been no survey literature devoted to fabric defect detection. The prior AVI surveys [3], [13], [15], [16] could not focus on the inspection of fabric defects, due to their wide coverage of the inspection problem. Among these, only the survey in [3] has included a short paragraph that discusses 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 the range of AVI techniques for other industrial products. Moreover, there have been several key developments in the AVI technique for fabric defects in the last ten years. In addition, due to the rapidly decreasing cost of sensing and computing power, several new algorithms have been proposed for fabric inspection. The fabric defect detection approaches are not limited to the images acquired from a digital camera; Sheen *et al.* [134] have presented an ultrasonic imaging system for textile web inspection, [135] illustrates the use of reflected infrared frequencies while the fabric inspection using a knowledge-based system to trace fabric defects have been proposed in [26], [142], [150].

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 fabric inspection rather than on actual inspection systems. However, only a few fabric inspection systems, although very expensive, are currently available in the market and some of these are summarized in [141].

IV. 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 the microscopic level, the inspection problem encountered in textured images becomes a 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 defect detection have been confined to rather deterministic images such as the ones used in printed circuit board 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 assumes 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 first introduced in Section IV-A, which is followed by spectral approaches in Section IV-B. 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 Section IV-C. Section V attempts to classify the scope of some of the proposed methods and their key challenges. Finally, Section VI summarizes the conclusions from this paper.

A. Statistical Approaches

The objective of defect detection is to separate the inspection image into 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 the 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 (FD), first-order statistics,

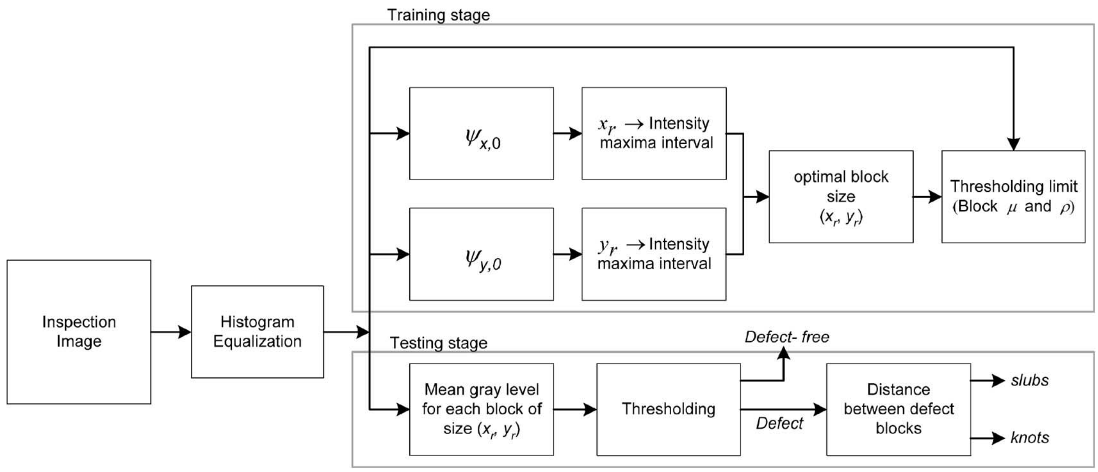

Fig. 3. Defect detection based on statistical block processing.

cross correlation, edge detection, morphological operations, cooccurrence 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.

1) Defect Detection Using FD: Conci and Proença [45] have used the estimate of FD on inspection images to detect fabric defects. In order to process large amounts of image data, they implemented the differential box counting method with a few modifications 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, suggesting 96% detection on eight types of defects. The localization accuracy of these detected defects is very poor and have high false alarm.

2) Defect Detection Using Bilevel 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 rise or fall momentarily, and the resultant peak or trough can be detected by thresholding. Norton-Wayne *et al.* [46], [47] have used this idea to detect fabric defects on textile web moving at a speed of one m 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 for clustered triggers generated after thresholding. Bradshaw [48] and Cho *et al.* [161] have also detailed fabric defect detection using bilevel thresholding. Stojanovic *et al.* [25] have also developed a fabric inspection system that uses thresholding, noise removal followed by local averaging to identify eight categories of defects with 86.2% accuracy, but 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 [49]. The advantage of defect detection techniques based on bilevel thresholding lies in its ease of implementation. However, such techniques fail to detect those defects that appear without altering the mean gray level in defect-free areas.

3) Defect Detection Using Gray-Level Statistics: Independent classifications of image pixels, as used in [46], is likely to perform poorly since locally there may not be sufficient information to make good decisions 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 and classifying these blocks into defect or defect-free classes 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 the autocorrelation function $(\psi_{x,0}, \psi_{y,0})$, as shown in Fig. 3, to select the optimal block size.

Another scheme used by Huart and Postaire [20] and is worth mentioning, uses a 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 that detailed in Section IV-A2. The thresholding limit is determined from the defect-free fabric, similar to [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 [51] have used a raised cosine filter to suppress high frequencies (harmonics) and retain the fundamental frequency corresponding to the periodicity of yarns. Bilevel thresholding on these filtered image subblocks 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 a color ring-projection algorithm for computational ease and demonstrated a defect detection that is invariant to the texture rotation. Chetverikov [52] has introduced the quantitative definition of maximal regularity, and has shown it to be consistent with human judgment [162] on the regularity of textures. The maximum regularity is derived from the gray-level statistics (periodicity autocorrelation function) of textile images. 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 that 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 the approaches in [20], [50], [51] is their computational simplicity, which makes them attractive for implementation using a simple general purpose computer. However, the utility of the 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) 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 a binary image. The binary image of a defect-free fabric (during training) is used to extract the optimal size and shape of structuring element (SE) using an autocorrelation function as detailed in Section IV-A3. 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 [53] have also detected fabric defects using laser-based morphological operations. This approach filters out the periodic structure of the fabric in the optical domain by inserting a Fourier lens after proper spatial filtering. Thus, the morphological operations are only performed on aperiodic image defects, unlike the case in [50] where the entire structure of the thresholded fabric image was utilized. However, the experimental results presented in [53] are on obvious defects and do not suggest any advantage over other available, less complex approaches.

5) Defect Detection Using Edge Detection: The distribution of the amount of edges per unit area is an important feature in the textured images. The amount of gray level transitions in the fabric image can represent lines, edges, point defects and other spatial discontinuities. These features have been used to detect fabric defects [54]–[56]. Conci and Proença [55] have used Sobel edge detection to detect fabric defects and compared the results with those based on thresholding and FD. However, they have not described their methodology and have only discussed their comparison. Lane [56] 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 nondefect 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 surfaces using the facet model appears in [73]. The design and implementation of application-specific integrated circuits for the edge detection-based real-time defect detection has been detailed in [99]. The defect detection approaches [54]–[56], [73] 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.

6) Defect Detection Using Normalized Cross-Correlation: The cross-correlation function provides a direct and accurate measure of similarity between two images. Any significant variation in the value of this measure indicates the presence of a defect. Bodnarova *et al.* [57] 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 [57], [58] are few and do not show any advantage over those based on first-order statistical moments in [20], [50].

7) Defect Detection Using Cooccurrence Matrix Features: Texture is a neighborhood property, therefore, spatial interactions among neighboring pixels have been used for the characterization of textures. Siew *et al.* [60] 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) [59]. The gray level cooccurrence matrix is one of the most popular statistical texture analysis tools and has also been used for the detection of surface defects on wood [61] and fabrics [62]. The classical approaches based on the estimation of statistical moments (e.g., mean and variance [20], [46]–[51]) or some other statistical parameters allow very quick characterization of fabric images. On the other hand, the methods based on higher order statistics (e.g., cooccurrence matrix [61]–[63], [65], [67], GLRLM, and GLDM) provide more information but are more demanding in terms of both computational and memory requirements.

Harlick *et al.* [64] have derived 14 features from the cooccurrence 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 [62] (four [63]) of these six features. Conners *et al.* [61] have used six features of the cooccurrence matrix, to identify nine different kinds of surface defects in wood. Tsai *et al.* [62] have detailed fabric defect detection while using only two features, i.e., angular second moment and contrast, and achieved a classification rate as high as 96%. Rösler [65] has also developed a real fabric defect detection system, using cooccurrence 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 cooccurrence 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 [66]. Bodnarova *et al.* [67] have examined this issue on the optimal displacement vector

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

$\boldsymbol{d}$ for fabric defect detection. The five elemental feature matrices [68], corresponding to the five features [69], is derived and subjected to a χ^2 significance test for defect declaration. Another related approach to detect magnetic disk defects using cooccurrence spectrum of fourth order rank appears in [70]. There are two major problems in the conventional use of the cooccurrence matrix in fabric defect detection (inefficient portioning of cooccurrence space and inefficient description of multipixel cooccurrence), which should be addressed to achieve the best possible performance for online fabric inspection. Also, the asymmetric cooccurrence matrix contains more information about texture orientation and therefore should be preferred than the symmetrical ones.

8) Defect Detection Using Eigenfilters: The information content of defect-free fabric image can also be extracted by registering the variations in an ensemble of macro windows within the image, independent of any judgment of its texture. Unser and Ade [71], [72] use this local information to construct eigenfilters for defect detection in textured materials. Monadjemi [157], [158] 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 [132]. 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 [156]. 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.

9) Defect Detection Using Local Linear Transforms: Several popular bidimensional 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.* [74] have compared the performance of 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 Section IV-A8, 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 in multiples of four. Therefore, pseudo-Hadamard transform has been used to obtain 3×3 and 5×5 masks by truncation of proper Hadamard masks of the required size. The results of their experiments [74] have compared favorably with the set of empirical filters introduced by Laws. However, their data set was limited to only two types of fabric defects and therefore their results are subjective and lack generality. Neubauer [75] 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 [76] are used to extract histogram features from every window of the image. These features are then used for the classification of the corresponding window into defect-free of defect class, using a three-layer neural network.

Őzdemir and Erçil [36] have implemented fabric defect detection using an approach that is a variation of the Karhunen-Loève (KL) transform or eigenfilters method described in Section IV-A8. Instead of using the eigenvectors of the covariance matrix, they have used the eigenvalues of the 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 subwindows [77]. 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.

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 an ascending order [79]. A 1 : 1 correspondence exists between the rank function and the related histogram, which does not exist between the 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 is a very efficient definition of rank-distances that can be efficiently computed. De Natale [78] has used rank order functions for the detection of artificially introduced defects in some Brodatz textures [80]. He introduced appropriate rank-distance functions, which proved to have a substantial advantage over the classical histogram-based approaches for defect detection. Another related work for the parquet slab grading using cumulative histogram is described in [7]. Desoli *et al.* [79] have demonstrated 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 [81], [82] to detect defects. The fabric texture information regarding spatial distribution and orientation, etc., is not uniquely determined from the knowledge of rank order functions. Because of such drawbacks, the rank order functions or classical histogram analysis have failed to generate any further interest for fabric defect detection.

11) Defect Detection Using Neural-Networks: Neural networks are among the best classifiers used for fault detection due to their nonparametric nature and ability to describe complex decision regions. The problem of fabric defect segmentation using feedforward neural networks (FFNs) 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 networks is described in [11] but is not adequately detailed. A framework for real-time visual inspection using the self-organizing map-based classifier with

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

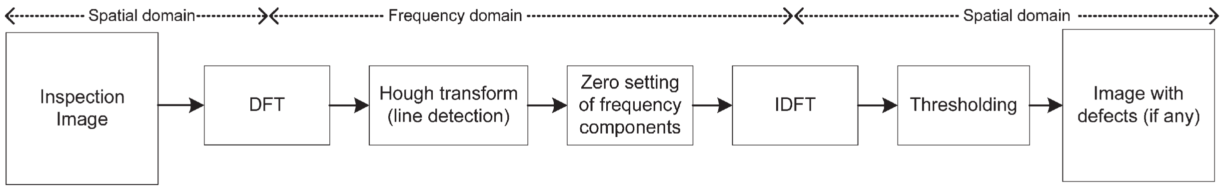

Fig. 4. Detection of fabric defects using DFT.

a log-likelihood dissimilarity measure is presented in [9]. The Support Vector Machines (SVMs) offer an 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 [137]. 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 intraclass diversity remains a major obstacle in using FFN [5], [11] and SVM [137] based approaches for online fabric inspection.

B. Spectral Approaches

Many common low-level statistical approaches such as edge detection break down for several fabric defects 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 the 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 [60] has suggested that it may be possible to find spatial-frequency domain features that are less sensitive to noise and intensity variations than those features extracted from the spatial domain. The psychophysical research has also indicated that the human visual system analyzes 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 the largest volume of references for fabric defect detection and are summarized in the following sections.

1) Defect Detection Using Discrete Fourier Transform (DFT): 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 [83]. Because of 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 [84] have used perfectly contiguous and nonoverlapping concentric rings of constant width to include various amounts of loosely localized frequency components. The authors [84] have used the local statistics of these 1-D signatures to monitor yarn densities, rather than defects, of woven fabrics. However, Chan and Pang [85] have detailed the usage of localized frequency components for the identification of real fabric defects. Tsai and Hu [86] 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 [87] have detected defects in the directional textures, such as fabrics and machined surfaces, using a combination of DFT and Hough transform [159]. 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 in the spatial domain. Thus, IDFT preserves only local anomalies (defects) if they appear in 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.

2) Defect Detection Using Optical Fourier Transform (OFT): 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 OFT is relatively easy and fast. The Fraunhoffer diffraction pattern of an object (fabric) is the Fourier transform of that object [88]. The luminous intensities of the zero- and first-order diffraction patterns are modulated by the existence of fabric defects [89]. Therefore, the fabric defect detection systems using the measurements of the first- and the zero-order intensities have been developed [90]–[93]. Ciamberlini *et al.* [94] have described the design of spatial filters: 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.* [95] have used pinhole type spatial filters on the OFT images to detect shadow mask defects of sizes as small as 500 μm^2.

The diameter of a laser beam employed to generate OFT images of the moving fabric cannot be too large relative the spacing of the weft and warp yarns in the fabric. The small beam diameter requires multiple optical systems [97] to cover the width of the fabric, which is very costly and complex. Therefore, Fomenko [96] has used high-speed swinging,

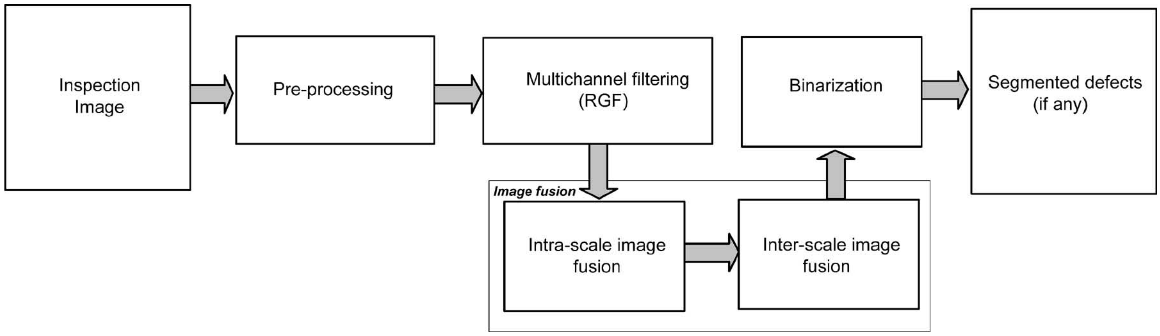

Fig. 5. Block diagram of the RGF-based web inspection system.

scanning and descanning 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.* [98] 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.

3) Defect Detection Using Windowed Fourier Transform (WFT): 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 WFT have been suggested for fabric defect detection. Campbell and Murtagh [100] have detailed a WFT-based method to detect defects on denim fabric samples. A 16×16 pixel 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 [101], [102]. Campbell *et al.* [103] have shown that the feature extraction using WFT and the subsequent decision mechanism has the potential for parallel implementation via a FFN structure. They have computed WFT features in a 32×32 pixel moving windows to detect denim fabric defects.

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 [104]: 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], [107]–[109], [139]. 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 [105], [106], [139] and [152], respectively. The real part of a Gabor filter has been shown to act as a blob detector. The mechanism of texture segmentation in human visual systems has been described with the Real Gabor Functions (RGFs) and the sigmoidal shaped nonlinearity in the retinal adaptations. Therefore, a bank of multiorientation and multiresolution RGF, followed by intra- and interscale image fusion (Fig. 5), is suggested to segment fabric defects [14], [154]. Kumar [1], [23] has also demonstrated that the dominant spectral component in defect-free fabric can be computed from the fast Fourier transform (FFT) decomposition and used to automatically select the center frequencies of Gabor filters.

5) Defect Detection Using Optimized Fir Filters: Some fabric defects that produce very subtle intensity transitions may be difficult to detect using the 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 more free parameters than an IIR or a Gabor filter and thus offers the 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.

6) Defect Detection Using Wigner Distributions: The Wigner distribution function is Fourier-like but has been shown to offer better conjoint resolution than Gabor or difference of Gaussians for conjoint 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

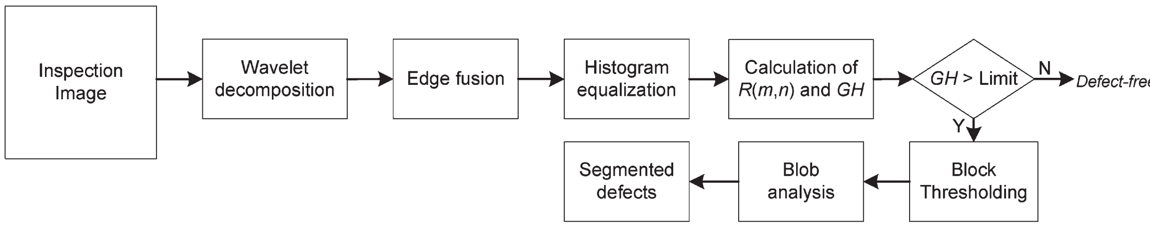

Fig. 6. Fabric defect segmentation using multiscale wavelet decomposition.

detect fabric defects. However, the computation time for this algorithm is stated to be about two min to inspect a 256 $\times$ 256 pixel image, which is prohibitive for use 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.

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 in 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 possesses 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 [110] have developed a fabric defect detection system that can detect defects as small as 0.2 in with an overall detection rate of 89%. Their defect detection scheme uses the low-pass and the high-pass "Daubechies" D2 filters [83]. The authors [110], [112] have shown that the two fractal-based measurements, local roughness $R(m, n)$ and global homogeneity, can be used to quantify surface characteristics of the real fabric images (Fig. 6). However, the selection of wavelet scales in [110], [112] is limited due to their dyadic nature and can pose problems in the accurate localization of defects. Therefore, multiscale representation of fabric image using B-spline transform is proposed [138] for defect detection.

Kim *et al.* [113] have described a fabric defect detection scheme using wavelet analysis on 1-D projection signals. The two 1-D signals from every inspection image 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 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.* [113] do not preserve the adjacency of features, except in the two directions of scanning. Therefore, 1-D signals generated from the inspection images using fractal scanning have been used for fabric defect detection [151]. 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 [29], [114]–[117] the usage of a fuzzy wavelet analysis technique employing fractal scanning. This approach generates the wavelet coefficients across several scales, 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 [29], [114]–[117] 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 [133] to identify fabric defects.

Jasper *et al.* [118], [155] 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], [121]. The design of such adaptive orthonormal wavelet bases has also been shown [124] to achieve the best performance in the characterization of fabric defects. The wavelet coefficients can also be selectively used to reconstruct the fabric image that is lacking in texture 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 [119] have used four-scale dyadic wavelet decomposition to extract features from 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 ICA has been investigated in [160]. Kumar and Gupta [120] 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 [111], [130] cannot detect defects that appear as subtle changes in fabric texture.

C. 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 processes, and textured images can be observed as the realizations or the samples from parametric probability distributions on the image space [122]. 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.

1) Defect Detection Using Gauss Markov Random Field (GMRF) Model: The stochastic models based on the GMRF have been successfully shown to model many natural and man-made textures [123]. Cohen *et al.* [153] 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 of the GMRF model parameters obtained from defect-free fabric. Fabric defect detection results using a similar approach have also been shown in [36], [122], and [125]. Őzdemir and Erçil [36], Baykut *et al.* [131] have implemented a 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 ten times faster than that based on KL transform (Section IV-A8). Attali and Cohen [126] have discussed stochastic modeling of textured images using the 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.

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. Brzakoviæ *et al.* [21], [22] have investigated the problem of defect detection in such randomly textured surfaces. Authors in [22] 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.

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.* [127] have used model-based clustering to detect relatively faint aligned defects in denim fabrics. In order to assess the evidence for the presence of a defect, Bayesian information criterion (BIC) [128] is used. The authors in [127] have used a chain of preprocessing operations, i.e., thresholding, opening, labeling, and object centroiding, before the estimation of BIC from the inspection images. The results from this paper suggest that the BIC value is invariably a reliable indicator for the presence of defects. Kong *et al.* [129] have used a new color-clustering scheme for the detection of defects on colored random textured images. This new scheme uses initial clustering involving K-mean clustering and a perceptual merging. As detailed in [129], 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.

V. Discussion

Quality assurance of textile materials using AVI 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 the 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], [139] have been evaluated on image samples with either of these resolutions (approximate): 1) 50 pixels per inch (PPI) [5], [139]; 2) 100 PPI [14], [23]; and 3) 200 PPI [5], [18]. Low-resolution images of the order of 50 PPI are accompanied by distortion due to the geometry of the imaging lens and/or nonuniform 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 [139] 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 [140] 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 two factors: 1) this method has shown a high degree of robustness for the detection of variety of defects and 2) 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).

TABLE I
SUMMARY OF IMAGE RESOLUTION AND OPERATIONS PER PIXEL FOR THE PROPOSED METHODS

Method / PPI	RGF [14], [23]	IGF [139]	AGF [139]	OF [18]	NN-1 [5]	NN-2 [5]	MRF [131]
50	√	√	√	NA	√(bad)	√	NA
100	√	X	√	√	√(bad)	X	√
200	√	X	√	√	√	X	NA
Operations per pixel (appox.)	$49 \times n$ ($n = 16$)	2	$81 \times 2 \times n$ ($n = 18$)	$170 \times n$ ($n = 2$)	285	2	7

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

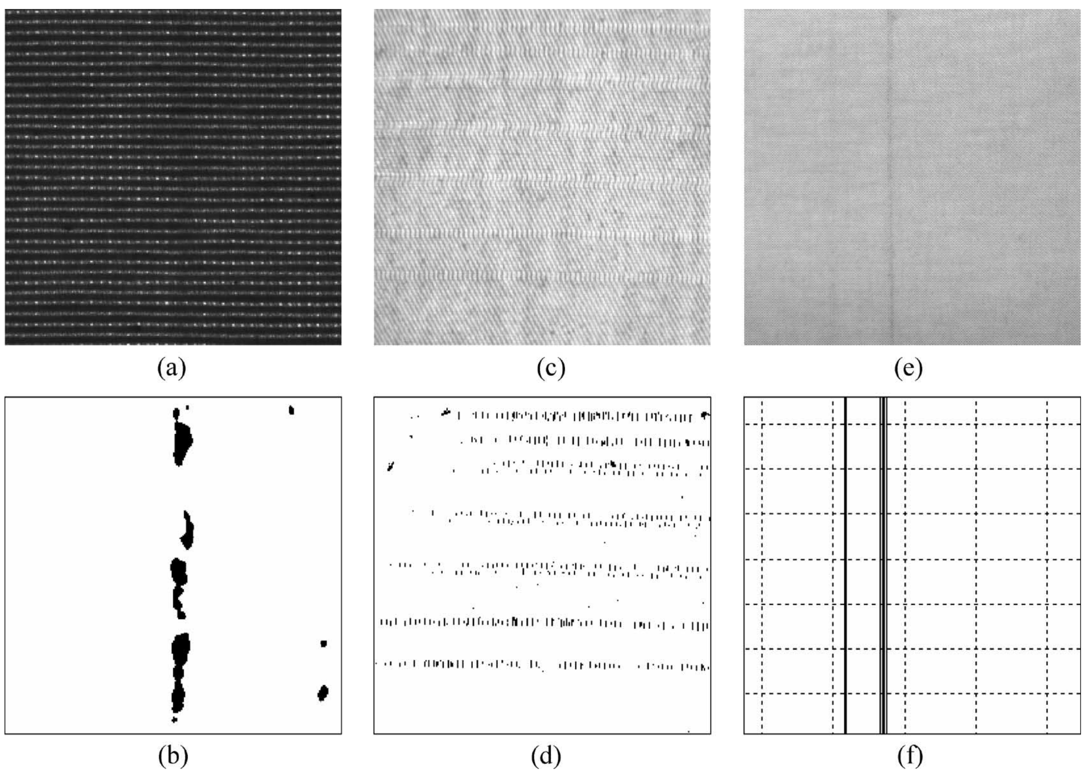

Fig. 7. Typical fabric image sample acquired at about (a) 200 PPI with defect tripe-warp (b), 100 PPI with defect mispick, and (c) 50 PPI with slack-end; corresponding detected defects can be seen in (b), (d), and (f).

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 [137] is 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 lose 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 use. 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, on high-resolution web images can be the judicious choice among methods in Table I. To sum up, the selection of a defect detection approach largely depends on the available computational power for online inspection. Fig. 7 illustrates [1] examples of typical fabric defects acquired with different imaging resolutions. Table I presents a summary on the effect of resolution for the proposed methods. The 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.* [131] have concluded that the MRF (nineth 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 cooccurrence matrix, correlation or FFT-based approaches. However, this comparison is very limited on a set of 25 images and the information about the image resolution is also missing. The comparisons in [17] and [131] 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 [80] and TILDAS [143] data set are quite convincing and suggest that these two measures can compliment each other. Therefore, a combination of these two approaches can offer the best performance for textile web inspection and is suggested for further investigation and comparison. Another aspect of the textile web inspection problem deals with the inspection of patterned webs and has remained largely unexplored. Most of the earlier attempts [136], [144]–[149] to this problem have focused on the 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 [144]. This problem requires the renewed attention using a 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.

VI. Conclusion

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 data set, performance evaluation and the nature of intended application, it is not prudent to explicitly declare the best available methods. Therefore, Section V 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 the entire width of the 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, wrinkle detection, pilling evaluation, design evaluation, defect classification, etc., has been largely excluded from this paper. There has been no 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 the 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.

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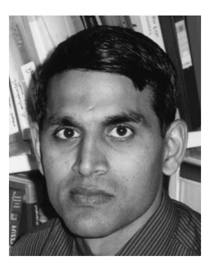
References

[1] A. Kumar, “Automated defect defection in textured materials,” Ph.D. dissertation, Dept. Elect. Electron. Eng., Univ. Hong Kong, Hong Kong, May 2001.
[2] R. G. Rosandich, *Intelligent Visual Inspection*. London, U.K.: Chapman & Hall, 1997.
[3] T. S. Newman and A. K. Jain, “A survey of automated visual inspection,” *Comput. Vis. Image Underst.*, vol. 61, no. 2, pp. 231–262, Mar. 1995.
[4] D.-M. Tsai and Y.-H. Tsai, “Defect detection in textured materials using color ring-projection correlation,” *Mach. Vis. Appl.*, vol. 13, pp. 194–200, 2003.
[5] A. Kumar, “Neural network based detection of local textile defects,” *Pattern Recognit.*, vol. 36, no. 7, pp. 1645–1659, Jul. 2003.
[6] D. Chetverikov and A. Henbury, “Finding defects in texture using regularity and local orientation,” *Pattern Recognit.*, vol. 35, no. 10, pp. 2165–2180, Oct. 2002.
[7] H. Kauppinen, “A two stage defect recognition method for parquet slab grading,” in *Proc. IEEE Conf. Pattern Recog.*, Barcelona, Spain, 2000, vol. 4, pp. 803–806.
[8] C.-C. Hung and I.-C. Chen, “Neural-fuzzy classification for fabric defects,” *Text. Res. J.*, vol. 71, no. 3, pp. 220–224, 2001.
[9] T. Mäenpää, M. Turtinen, and M. Pietikäinen, “Real-time surface inspection by texture,” *Real-Time Imaging*, vol. 9, no. 5, pp. 289–296, Oct. 2003.
[10] B. N. Nickolay and H. Schmalfuß, “Automatic fabric inspection—Utopia or reality?” *Melliand-Text.ber.*, vol. 73, pp. 33–37, 1993.
[11] D. Rohrmus, “Invariant web defect detection and classification system,” in *Proc. IEEE Conf. Comput. Vis. Pattern Recog.*, Jun. 2000, vol. 2, pp. 794–795.
[12] L. Occhipinti, G. Spoto, M. Branciforte, and F. Doddo, “Defects detection and characterization by using cellular neural networks,” in *Proc. ISCAS*, 2001, pp. 481–484.
[13] A. D. H. Thomas, M. G. Rodd, J. D. Holt, and C. J. Neill, “Real-time industrial inspection: A review,” *Real-Time Imaging*, vol. 1, no. 2, pp. 139–158, Jun. 1995.
[14] A. Kumar and G. Pang, “Fabric defect segmentation using multichannel blob detectors,” *Opt. Eng.*, vol. 39, no. 12, pp. 3176–3190, Dec. 2000.
[15] R. T. Chin and C. A. Harlow, “Automated visual inspection: A survey,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. PAMI-4, no. 6, pp. 557–573, Jun. 1982.
[16] R. T. Chin, “Automated visual inspection: 1981 to 1987,” *Commun. Vis. Graph. Image Process.*, vol. 41, no. 3, pp. 346–381, Mar. 1988.
[17] A. Bodnarova, M. Bennamoun, and S. J. Latham, “Optimal Gabor filters for textile flaw detection,” *Pattern Recognit.*, vol. 35, no. 12, pp. 2973–2991, Dec. 2002.

[18] A. Kumar and G. Pang, "Defect detection in textured materials using optimized filters," *IEEE Trans. Syst., Man, Cybern. B, Cybern.*, vol. 32, no. 5, pp. 553–570, Oct. 2002.
[19] K. Y. Song, M. Petrou, and J. Kittler, "Texture crack detection," *Mach. Vis. Appl.*, vol. 8, no. 1, pp. 63–76, 1995.
[20] J. Huart and J.-G. Postaire, "Integration of computer vision on to weavers for quality control in the textile industry," *Proc. SPIE*, vol. 2183, pp. 155–163, Feb. 1994.
[21] D. P. Brzaković, P. R. Bakić, N. S. Vuiovic, and H. Sari-Sarraf, "A generalized development environment for inspection of web materials," in *Proc. IEEE Int. Conf. Robot. Autom.*, Albuquerque, NM, Apr. 1997, pp. 1–8.
[22] D. Brzakovic, N. Vujovic, and A. Liakopoulos, "An approach to quality control of texture web materials," *Proc. SPIE*, vol. 2597, pp. 60–69, Oct. 1995.
[23] A. Kumar, "Automated inspection of textured web materials using real Gabor functions," in *Proc. 2nd SPIE ICIG*, Hefei, China, Aug. 2002, pp. 59–62.
[24] D.-M. Tsai and B. Hsiao, "Automatic surface inspection using wavelet reconstruction," *Pattern Recognit.*, vol. 34, no. 6, pp. 1285–1305, Jun. 2001.
[25] R. Stojanovic, P. Mitropulos, C. Koulamas, Y. Karayiannis, S. Koubias, and G. Papadopoulos, "Real-time vision-based system for textile fabric inspection," *Real-Time Imaging*, vol. 7, no. 6, pp. 507–518, Dec. 2001.
[26] K. Srinivasan, P. H. Dastor, P. Radhakrishnaihan, and S. Jayaraman, "FDAS: A knowledge-based frame detection work for analysis of defects in woven textile structures," *J. Text. Inst.*, vol. 83, no. 3, pp. 431–447, 1992.
[27] *Standard method for grading spun yarns for appearance*, Apr. 2000 ASTM D2255-96.
[28] A. Nevel, K. W. Gordon, and D. Bonneau, "System and method for electronically evaluating predicted qualities," U.S. Patent 6 130 746, Oct. 2000.
[29] J. L. Dorrity and G. Vachtsevanos, "On-line defect detection for weaving systems," in *Proc. IEEE Annu. Tech. Conf. Textile, Fiber, Film Ind.*, May 1996, pp. 1–6.
[30] B. G. Batchelor, "Lighting and viewing techniques," in *Automated Visual Inspection*, B. G. Batchelor, D. A. Hill, and D. C. Hodgson, Eds. Amsterdam, The Netherlands: North Holland, 1985.
[31] J. W. Roberts, S. D. Rose, G. Jullian, L. Nicholas, P. T. Jenkins, S. G. Chamberlin, G. Maroscher, R. Mantha, and D. J. Litwiller, "A PC-based real time defect imaging system for high speed web inspection," *Proc. SPIE*, vol. 1907, pp. 164–176, 1993.
[32] H. A. Bayer, "Performance analysis of CCD-cameras for industrial inspection," *Proc. SPIE*, vol. 1989, pp. 40–49, 1993.
[33] DALSA Inc., *1998–1999 DALSA Databook*. [Online]. Available: http://www.dalsa.com
[34] A. Kumar, "Inspection of surface defects using optimal FIR filters," in *Proc. ICASSP*, Hong Kong, Apr. 2003, pp. 241–244.
[35] G. Pang, R. Wong, H. Liu, T. Kwan, and A. Kumar, "CAVIS: A low-cost fabric defect inspection machine based on Machine Vision," in *Proc. Asian Textile Conf.*, Aug. 2001, pp. 11–16.
[36] S. Őzdemir and A. Erçil, "Markov random fields and Karhunen-Loève transforms for defect inspection of textile products," in *Proc. IEEE Conf. EFTA*, Nov. 1996, vol. 2, pp. 697–703.
[37] Y. A. Karayiannis, R. Stojanovic, P. Mitropoulos, C. Koulamas, T. Stouraitis, S. Koubias, and G. Papadopoulos, "Defect detection and classification on web textile fabric using multiresolution decomposition and neural networks," in *Proc. IEEE Int. Conf. Electron., Circuits Syst.*, Sep. 1999, pp. 765–768.
[38] D. Wilson, A. Greig, J. Gilby, and R. Smith, "Using uncertainty techniques to aid defect classification in an automated visual inspection system," in *IEE Colloq. Ind. Inspection*, Feb. 1997, pp. 2/1–2/10.
[39] X. Z. Yang, G. Pang, and N. Yung, "Fabric defect detection using adaptive wavelet," in *Proc. ICASSP*, 2001, vol. 6, pp. 3697–3700.
[40] G. Pang and A. Kumar, "Wavelet based detection of local textile defects," in *Proc. 8th IEEE Int. Conf. M2VIP*, Aug. 2001, pp. 428–431.
[41] R. M. Harlick, "Statistical and structural approaches to texture," *Proc. IEEE*, vol. 67, no. 5, pp. 786–804, May 1979.
[42] R. C. Gonzalez and M. G. Thomason, *Syntactic Pattern Recognition: An Introduction*. Reading, MA: Addison-Wesley, 1982.
[43] A. M. Darwish and A. K. Jain, "A rule based approach for visual pattern inspection," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 10, no. 1, pp. 56–68, Jan. 1988.
[44] M. Tuceryan and A. K. Jain, "Texture analysis," in *Handbook of Pattern Recognition and Computer Vision*, C. H. Chan, L. F. Pau, and P. S. P. Wang, Eds. Singapore: World Scientific, 1993, ch. 2, pp. 235–276.
[45] A. Conci and C. B. Proença, "A fractal image analysis system for fabric inspection based on box-counting method," *Comput. Netw. ISDN Syst.*, vol. 30, no. 20, pp. 1887–1895, Nov. 1998.
[46] L. Norton-Wayne, M. Bradshaw, and A. J. Jewell, "Machine vision inspection of web textile fabric," in *Proc. Brit. Mach. Vis. Conf.*, Leeds, U.K., Sep. 1992, pp. 217–226.
[47] L. Norton-Wayne, M. Bradshaw, and C. Sandby, "Machine vision for the automated inspection of web materials," *Proc. SPIE*, vol. 1989, pp. 2–13, 1993.
[48] M. Bradshaw, "The application of machine vision to the automated inspection of knitted fabrics," *Mechatronics*, vol. 5, no. 2/3, pp. 233–243, 1995.
[49] L. Macaire and J. G. Postaire, "Flaw detection on galvanized metallic strips in real-time by adaptive thresholding," *Proc. SPIE*, vol. 2183, pp. 14–23, 1993.
[50] Y. F. Zhang and R. R. Bresee, "Fabric defect detection and classification using image analysis," *Text. Res. J.*, vol. 65, no. 1, pp. 1–9, Jan. 1995.
[51] T. Thomas and M. Cattoen, "Automatic inspection of simply patterned materials in the textile industry," *Proc. SPIE*, vol. 2183, pp. 2–12, Feb. 1994.
[52] D. Chetverikov, "Pattern regularity as a visual key," *Image Vis. Comput.*, vol. 18, no. 12, pp. 975–985, Sep. 2000.
[53] B. Mallick-Goswami and A. K. Datta, "Detecting defects in fabric with laser-based morphological image processing," *Text. Res. J.*, vol. 70, no. 9, pp. 758–762, Sep. 2000.
[54] W. J. Jasper and H. Potapalli, "Image analysis of mispicks in woven fabrics," *Text. Res. J.*, vol. 65, no. 11, pp. 683–692, 1995.
[55] A. Conci and C. B. Proença, "A computer vision approach for textile inspection," *Text. Res. J.*, vol. 70, no. 4, pp. 347–350, Apr. 2000.
[56] J. S. Lane, "Textile fabric inspection system," U.S. Patent 5 774 177, Jun. 30, 1998.
[57] A. Bodnarova, M. Bennamoun, and K. K. Kubik, "Defect detection in textile materials based on aspects of HVS," in *Proc. IEEE SMC Conf.*, San Diego, CA, Oct. 1998, pp. 4423–4428.
[58] M. Bennamoun and A. Bodnarova, "Automatic visual inspection and flaw detection in textile materials: Past, present and future," in *Proc. IEEE Conf. SMC*, 1998, pp. 4340–4343.
[59] R. W. Conners and C. A. Harlow, "A theoretical comparison of texture algorithms," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. PAMI-2, no. 3, pp. 204–222, May 1980.
[60] L. H. Siew, R. M. Hodgson, and E. J. Wood, "Texture measures for carpet wear assessment," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 10, no. 1, pp. 92–105, Jan. 1988.
[61] R. W. Conners, C. W. McMillan, K. Lin, and R. E. Vasquez-Espinosa, "Identifying and locating surface defects in wood: Part of an automated lumber processing system," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. PAMI-5, no. 6, pp. 573–583, Nov. 1983.
[62] I. Tsai, C. Lin, and J. Lin, "Applying an artificial neural network to pattern recognition in fabric defects," *Text. Res. J.*, vol. 65, no. 3, pp. 123–130, Mar. 1995.
[63] A. L. Amet, A. Ertüzün, and A. Erçil, "Texture defect detection using subband domain co-occurrence matrices," in *Proc. IEEE Southwest Symp. Image Anal. Interpretation*, Apr. 1998, pp. 205–210.
[64] R. M. Harlick, K. Shanmugam, and I. Dinstein, "Textural features for image classification," *IEEE Trans. Syst., Man, Cybern.*, vol. 3, no. 6, pp. 610–621, Nov. 1973.
[65] R. N. U. Rösler, "Defect detection in fabrics by image processing," *Melliand-Text.ber.*, vol. 73, p. E292, 1992.
[66] S. W. Zucker and D. Terzopoulos, "Finding structure in co-occurrence matrices for texture analysis," in *Image Modelling*, A. Rosenfield, Ed. New York: Academic, Jan. 1990, pp. 423–445.
[67] A. Bodnarova, J. A. Williams, M. Bennamoun, and K. K. Kubik, "Optimal textural features for flaw detection in textile materials," in *Proc. IEEE TENCON Conf.*, Brisbane, Australia, Dec. 1997, pp. 307–310.
[68] R. F. Walker, P. Jackway, and I. D. Longstaff, "Improving co-occurrence matrix feature discrimination," in *Proc. Conf. DICTA*, A. Meader and B. Lovell, Eds., Brisbane, Australia, Dec. 1995, pp. 643–648.
[69] A. Bodnarova, J. A. Williams, M. Bennamoun, and K. K. Kubik, "Detection of flaws in textiles by the use of texture statistics," in *Proc. 4th Conf. DICTA*, Auckland, New Zealand, Dec. 1997, pp. 237–242.
[70] L. Hepplewhite and T. J. Stonham, "Surface inspection using texture segmentation," in *IEE Colloq. Texture Classification: Theory Appl.*, 1994, pp. 589–592.
[71] M. Unser and F. Ade, "Feature extraction and decision procedure for automated inspection of textured materials," *Pattern Recognit. Lett.*, vol. 2, no. 3, pp. 181–191, Mar. 1984.

[72] F. Ade, "Application of principal component analysis to the inspection of industrial goods," *Proc. SPIE*, vol. 397, pp. 216–223, 1983.
[73] B. R. Abidi, H. Sari-Sarraf, J. S. Goddard, M. A. Haunt, *Facet model and mathematical morphology for surface characterization*. Scientific Literature Digital Library. [Online]. Available: http://citeseer.ist.psu.edu/284961.html
[74] F. Ade, N. Lins, and M. Unser, "Comparison of various filter sets for defect detection in textiles," in *Proc. 7th Int. Conf. Pattern Recog.*, Montreal, QC, Canada, 1984, vol. 1, pp. 428–431.
[75] C. Neubauer, "Segmentation of defects in textile fabric," in *Proc. 11th Int. Conf. Pattern Recog.*, The Hague, The Netherlands, Aug. 1992, pp. 688–691.
[76] E. R. Davies, *Machine Vision: Theory, Algorithms, and Practicalities*, 2nd ed. New York: Academic, 1997, pp. 569–572.
[77] J. Strand and T. Taxt, "Local frequency features for texture classification," *Pattern Recognit.*, vol. 27, no. 10, pp. 1397–1406, Oct. 1994.
[78] F. G. B. De Natale, "Rank-order functions for the fast detection of texture faults," *Int. J. Pattern Recogn. Artif. Intell.*, vol. 10, no. 8, pp. 971–984, 1986.
[79] G. S. Desoli, S. Fioravanti, R. Fioravanti, and D. Corso, "A system for automated visual inspection of ceramic tiles," in *Proc. IEEE IECON*, 1993, vol. 3, pp. 1871–1876.
[80] P. Brodatz, *Texture: A Photographic Album for Artists and Designers*. New York: Dover, 1956.
[81] C. Boukouvalas, J. Kittler, R. Marik, and M. Petrou, "Color grading of randomly textured ceramic tiles using color histogram," *IEEE Trans. Ind. Electron.*, vol. 46, no. 1, pp. 219–226, Feb. 1999.
[82] L. Bergsa, N. Duffy, G. Laecy, and M. Mazo, "Industrial inspection using Gaussian functions in a colour space," *Image Vis. Comput.*, vol. 18, no. 12, pp. 951–957, Sep. 2000.
[83] R. N. Bracewell, *The Fourier Transform and Its Applications*, 3rd ed. Boston, MA: McGraw-Hill, 2000.
[84] H. Sari-Sarraf and J. S. Goddard, "On-line optical measurement and monitoring of yarn density in woven fabrics," *Proc. SPIE*, vol. 2899, pp. 444–452, 1996.
[85] C. H. Chan and G. Pang, "Fabric defect detection by Fourier analysis," *IEEE Trans. Ind. Appl.*, vol. 36, no. 5, pp. 1267–1276, Sep./Oct. 2000.
[86] I. S. Tsai and M. C. Hu, "Automatic inspection of fabric defects using an artificial neural network technique," *Text. Res. J.*, vol. 66, no. 7, pp. 474–482, Jul. 1996.
[87] D.-M. Tsai and C.-Y. Heish, "Automated surface inspection for directional textures," *Image Vis. Comput.*, vol. 18, no. 1, pp. 49–62, Dec. 1999.
[88] E. J. Wood, "Applying Fourier and associated transforms to pattern characterization in textiles," *Text. Res. J.*, vol. 60, no. 4, pp. 212–220, Apr. 1990.
[89] B. Mallik and A. K. Datta, "Defect detection in fabrics with a joint transform correlation technique: Theoretical basis and simulation," *Text. Res. J.*, vol. 69, no. 11, pp. 829–835, Nov. 1999.
[90] D. C. Mead, H. L. Kasdan, and J. L. Dorrity, "Method for automatic fabric inspection," U.S. Patent 4 124 300, Nov. 7, 1978.
[91] C. Castellini, F. Francini, G. Longobardi, and B. Tirbilli, "On-line textile quality control using optical Fourier transform," *Opt. Lasers Eng.*, vol. 24, no. 1, pp. 19–32, 1992.
[92] S. Ribolzi, J. Merckle, and J. Gresser, "Real-time fault detection on textiles using opto-electronic processing," *Text. Res. J.*, vol. 63, no. 2, pp. 61–71, 1993.
[93] C. Ciamberlini, F. Francini, G. Longobardi, P. Poggi, P. Sansoni, and T. Tiribili, "Weaving defect detection by Fourier imaging," *Proc. SPIE*, vol. 2786, pp. 9–18, 1996.
[94] C. Ciamberlini, F. Francini, G. Longobardi, P. Sansoni, and B. Tiribili, "Defect detection in textured materials by optical filtering with structured detectors and self-adaptable masks," *Opt. Eng.*, vol. 35, no. 3, pp. 835–844, Mar. 1996.
[95] S. Kim, S. Lee, and D. Yoon, "Rapid pattern inspection of shadow masks by machine vision integrated with Fourier optics," *Opt. Eng.*, vol. 36, no. 12, pp. 3309–3311, Dec. 1997.
[96] S. M. Fomenko, "Coherent scanning system for fabric inspection," U.S. Patent 4 057 351, Nov. 8, 1977.
[97] D. F. Clark and D. Casasent, "Practical optical Fourier analysis for high speed inspection," *Opt. Eng.*, vol. 27, no. 5, pp. 365–371, May 1988.
[98] L. H. Hoffer, F. Francini, B. Tiribilli, and G. Longobardi, "Neural networks for the optical recognition of defects in cloth," *Opt. Eng.*, vol. 35, no. 11, pp. 3183–3190, Nov. 1996.
[99] M. Robert, M. Paindavoine, and P. Gorria, "An edge detection ASIC for real time defect detection," in *Proc. 5th Annu. IEEE Int. Conf. ASIC*, Rochester, NY, Sep. 1992, pp. 193–196.
[100] J. G. Campbell and F. Murtagh, "Automatic visual inspection of woven textiles using a two-stage defect detector," *Opt. Eng.*, vol. 37, no. 9, pp. 2536–2542, Sep. 1998.
[101] C. W. Therrien, *Decision, Estimation, and Classification*. New York: Wiley, 1989.
[102] J. G. Campbell, A. A. Hasim, and F. D. Murtagh, *Flaw detection in woven textiles using space-dependent Fourier transform*. Coleraine, Ireland: Faculty Informatics, Univ. Ulster, May 1997. Magee College Preprint INFM-97-004.
[103] J. G. Campbell, A. A. Hasim, T. M. McGinnity, and T. F. Lunney, *Flaw detection in woven textiles by neural network*. Coleraine, Ireland: Faculty Informatics, Univ. Ulster, May 1997. Magee College Preprint INFM-97-002.
[104] A. C. Bovik, M. Clark, and W. S. Geisler, "Multichannel texture analysis using localized spatial filters," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 12, no. 1, pp. 55–73, Jan. 1990.
[105] J. Escofet, R. Navarro, M. S. Millan, and J. Pladelloreans, "Detection of local defects in textiles webs using Gabor filters," *Proc. SPIE*, vol. 2785, pp. 163–170, Jun. 1996.
[106] J. Escofet, R. Navarro, M. S. Millan, and J. Pladelloreans, "Detection of local defects in textiles webs using Gabor filters," *Opt. Eng.*, vol. 37, no. 8, pp. 2297–2307, Aug. 1998.
[107] A. Kumar and G. Pang, "Defect detection in textured materials using Gabor filters," in *Conf. Rec. 35th IEEE IAS Annu. Meeting*, Rome, Italy, Oct. 2000, pp. 1041–1047.
[108] A. Bodnarova, M. Bennamoun, and S. J. Latham, "A constrained minimisation approach to optimise Gabor filters for detecting flaws in woven textiles," in *Proc. IEEE ICASSP*, Brisbane, Australia, Jun. 2000, vol. 6, pp. 3606–3609.
[109] A. Bodnarova, M. Bennamoun, and S. J. Latham, "Textile flaw detection using optimal Gabor filters," in *Proc. 15th Int. Conf. Pattern Recog.*, Brisbane, Australia, Sep. 2000, vol. 4, pp. 799–802.
[110] H. Sari-Sarraf and J. S. Goddard, "Vision systems for on-loom fabric inspection," *IEEE Trans. Ind. Appl.*, vol. 35, no. 6, pp. 1252–1259, Nov./Dec. 1999.
[111] Y. Han and P. Shi, "An adaptive level-selecting wavelet transform for texture defect detection," *Image Vis. Comput.*, vol. 25, no. 8, pp. 1239–1248, Aug. 2007.
[112] D. Brzakovic and H. Sari-Sarraf, "Automated inspection of web materials: A case study," *Proc. SPIE*, vol. 2183, pp. 214–223, 1994.
[113] S. Kim, M. H. Lee, and K. B. Woo, "Wavelet analysis to defects detection in weaving processes," in *Proc. IEEE Int. Symp. Ind. Electron.*, Jul. 1999, vol. 3, pp. 1406–1409.
[114] J. G. Vachtsevanos, M. Mufti, and J. L. Dorrity, "Method and apparatus for analyzing an image to detect and identify defects," U.S. Patent 5 815 198, Sep. 29, 1998.
[115] M. Mufti, "Fault detection and identification using fuzzy wavelets," Ph.D. dissertation, Dept. Elect. Comput. Eng., Georgia Inst. Technol., Atlanta, GA, Aug. 1995.
[116] M. Mufti and J. G. Vachtsevanos, "Automated fault detection and identification using a fuzzy-wavelet analysis technique," in *Proc. IEEE Conf. Syst. Readiness: Test Technol. for 21st Century, AUTOTESTCON*, 1995, pp. 169–175.
[117] J. L. Dorrity and J. G. Vachtsevanos, "In-process fabric defect detection and identification," in *Proc. Mechantronics*, 1998, pp. 745–750.
[118] W. J. Jasper, S. J. Garnier, and H. Potapalli, "Texture characterization and defect detection using adaptive wavelets," *Opt. Eng.*, vol. 35, no. 11, pp. 3140–3149, Nov. 1996.
[119] G. Lambert and F. Bock, "Wavelet methods for texture defect detection," in *Proc. IEEE Int. Conf. Image Process.*, Oct. 1997, vol. 3, pp. 201–204.
[120] A. Kumar and S. Gupta, "Real time DSP based identification of surface defects using content-based imaging technique," in *Proc. IEEE Conf. Ind. Technol.*, Jan. 2000, vol. 2, pp. 113–118.
[121] X. Z. Yang, G. Pang, and N. Yung, "Discriminative fabric defect detection using adaptive wavelet," *Opt. Eng.*, vol. 41, no. 12, pp. 3116–3126, Dec. 2002.
[122] F. S. Cohen and Z. Fan, "Rotation and scale invariant texture classification," in *Proc. IEEE Conf. Robot. Autom.*, Apr. 1988, vol. 3, pp. 1394–1399.
[123] R. Cross and A. K. Jain, "Markov random field texture models," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. PAMI-5, no. 1, pp. 25–39, Jan. 1983.
[124] X. Yang, G. Pang, and N. Yung, "Discriminative training approaches to fabric defect classification based on wavelet transform," *Pattern Recognit.*, vol. 37, no. 5, pp. 889–899, May 2004.

[125] G. Yunan, "Study on image analysis for fabric defects," Ph.D. dissertation, China Textile Univ., Shanghai, China, 1999.
[126] S. F. Attali and F. S. Cohen, "Surface inspection based on stochastic modeling," *Proc. SPIE*, vol. 665, pp. 46–52, 1986.
[127] J. G. Campbell, C. Fraley, F. Murtagh, and A. E. Raftery, "Linear flaw detection in woven textiles using model-based clustering," Dept. Statistics, Univ. Washington, Seattle, WA, Tech. Rep. 314, Jul. 1996, pp. 1–15.
[128] R. E. Kassand and A. E. Raftery, "Bayes factors," *J. Amer. Stat. Assoc.*, vol. 90, no. 430, pp. 773–795, Jun. 1995.
[129] K. Y. Kong, J. Kittler, M. Petrou, and I. Ng, "Chromato-structural approach towards surface defect detection in random textured images," *Proc. SPIE*, vol. 2183, pp. 193–204, Feb. 1994.
[130] H. Fujiwara, Z. Zhang, and K. Hashimoto, "Towards automated inspection of textile surfaces: Removing the textural information by using wavelet shrinkage," in *Proc. Int. Conf. Robot. Autom.*, Seoul, Korea, May 2001, pp. 3529–3534.
[131] A. Baykut, A. Atalay, A. Erçil, and M. Güler, "Real-time defect inspection of textured surfaces," *Real-Time Imaging*, vol. 6, no. 1, pp. 17–27, Feb. 2000.
[132] G. Mamic and M. Bennamoun, "Automatic flaw detection in textiles using a Neyman-Pearson detector," in *Proc. Int. Conf. Pattern Recog.*, Barcelona, Spain, Sep. 2000, pp. 767–770.
[133] A. Kumar and G. Pang, "Identification of surface defects in textured materials using wavelet packets," in *Conf. Rec. 36th IEEE IAS Annu. Meeting*, Chicago, IL, Sep. 2001, pp. 247–251.
[134] S. H. Sheen, H. T. Chien, W. P. Lawrence, and A. C. Raptis, "Ultrasonic imaging system for in-process fabric defect detection," U.S. Patent 5 665 907, Sep. 9, 1997.
[135] F. A. Cole and R. L. Deak, "Defect detection system," U.S. Patent 4 249 081, Feb. 3, 1981.
[136] L. Tao, P. Witty, and T. King, "Machine vision in the inspection of patterned textile webs," in *IEE Colloq. Ind. Inspection*, London, U.K., Feb. 1997, pp. 1–5.
[137] A. Kumar and H. C. Shen, "Texture inspection for defects using neural networks and support vector machines," in *Proc. ICIP*, Rochester, NY, Sep. 2002, pp. 353–356.
[138] P. Zeng and T. Hirata, "On-loom fabric inspection using multi-scale differentiation filtering," in *Conf. Rec. 37th IEEE IAS Annu. Meeting*, Pittsburgh, PA, Oct. 2002, pp. 320–326.
[139] A. Kumar and G. Pang, "Defect detection in textured materials using Gabor filters," *IEEE Trans. Ind. Appl.*, vol. 38, no. 2, pp. 425–440, Mar. 2002.
[140] M. D. Heath, S. Sarkar, T. Sanocki, and K. W. Bowyer, "A robust visual method for assessing the relative performance of edge-detection algorithms," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 19, no. 12, pp. 1338–1359, Dec. 1997.
[141] A. Dockery, *Automated Fabric Inspection: Assessing the Current State of the Art*, Jul. 2001. [Online]. Available: http://techexchange.com/thelibrary/FabricScanning.html
[142] I.-S. Tsai, C.-H. Lin, and J.-J. Lin, "Application of fuzzy set theory to diagnosis system for tracing breakdown causes in weaving," *Proc. Int. IEEE Conf. Ind. Autom. Control*, pp. 200–207, May 1995.
[143] *TILDA Textile Texture Database, Texture Analysis Working Group of DFG*. [Online]. Available: http://lmb.informatik.uni-freiburg.de
[144] C. Sanby, L. Norton-Wayne, and R. Harwood, "The automated inspection of lace using machine vision," *Mechatronics*, vol. 5, no. 2/3, pp. 215–231, 1995.
[145] H. R. Yazdi, "Automatic visual inspection of lace," Ph.D. dissertation, Univ. Birmingham, Birmingham, U.K., 1999.
[146] L. G. Tao and T. G. King, "Modified Hough transforms for feature recognition on deformable patterned materials," *Image Vis. Comput.*, vol. 12, pp. 465–472, Sep. 1994.
[147] H. R. Yazdi and T. G. King, "Application of vision in the loop for inspection of lace fabrics," *Real-Time Imaging*, vol. 4, no. 5, pp. 317–332, Oct. 1998.
[148] U. Farooq, T. G. King, P. H. Gaskell, and N. Kapur, "Machine vision using image data feedback for fault detection in complex deformable webs," *Trans. Inst. Meas. Control*, vol. 26, no. 2, pp. 119–137, 2004.
[149] M. A. Haunt, J. S. Goddard, K. W. Hylton, T. P. Karnowski, R. K. Richards, M. L. Simpson, K. W. Tobin, and D. A. Treece, *Imaging tristimulus colorimeter evaluation of color in printed textiles*. Scientific Literature Digital Library. [Online]. Available: http://citeseer.ist.psu.edu/283940.html
[150] P. Perner, "A knowledge-based image-inspection system for automatic defect recognition, classification, and process diagnosis," *Mach. Vis. Appl.*, vol. 7, no. 3, pp. 135–147, Sep. 1994.
[151] J. G. Vachtsevanos, J. L. Dorrity, P. Wang, J. Echauz, and M. Mufti, "Method and apparatus for analyzing an image to detect and identify patterns," U.S. Patent 6 650 779, Nov. 18, 2003.
[152] C. Beirão and M. Figueiredo, "Defect detection in textile images using Gabor filters," in *Proc. ICIAR*, 2004, vol. 3212, pp. 841–848.
[153] F. S. Cohen, Z. Fan, and S. Attali, "Automated inspection of textile fabrics using textural models," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 8, no. 13, pp. 803–808, Aug. 1991.
[154] A. Kumar and G. Pang, "Defect detection system for quality assurance using automated visual inspection," U.S. Patent 6 753 965, Jun. 22, 2004.
[155] W. Jasper, J. Joines, and J. Brenzovich, "Fabric defect detection using a genetic algorithm tuned wavelet filter," *J. Text. Inst.*, vol. 96, no. 1, pp. 43–54, 2004.
[156] O. G. Sezer, A. Ertüzün, and A. Erçil, "Independent component analysis for texture defect detection," in *Proc. 6th OGRW*, Novosibirsk, Russia, Nov. 2003, pp. 210–213.
[157] A. Monadjemi, "Towards efficient texture classification and abnormality detection," Ph.D. dissertation, Dept. Comput. Sci., Univ. Bristol, Bristol, U.K., Oct. 2004.
[158] A. Monadjemi, M. Mirmedhi, and B. Thomas, "Restructured eigenfilter matching for novelty detection in random textures," in *Proc. 15th British Mach. Vis. Conf.*, Sep. 2004, pp. 637–646.
[159] K-J. Choi, Y-H. Lee, J.-W. Moon, C.-K. Park, and F. Harashima, "Development of an automatic stencil inspection system using modified Hough transform and fuzzy logic," *IEEE Trans. Ind. Electron.*, vol. 54, no. 1, pp. 604–611, Feb. 2007.
[160] A. Serdaroglu, A. Ertuzun, and A. Ercil, "Defect detection in textile fabric images using wavelet transforms and independent component analysis," *Pattern Recognit. Image Anal.*, vol. 16, no. 1, pp. 61–64, Jan. 2006.
[161] C.-S. Cho, B.-M. Chung, and M.-J. Park, "Development of real-time vision-based fabric inspection system," *IEEE Trans. Ind. Electron.*, vol. 52, no. 4, pp. 1073–1079, Aug. 2005.
[162] O. G. Sezer, A. Ercil, and A. Ertuzun, "Using perceptual relation of regularity and anisotropy in the texture with independent component model for defect detection," *Pattern Recognit.*, vol. 40, no. 1, pp. 121–133, Jan. 2007.



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