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Computer vision-based fabric defect analysis and measurement

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Abstract: Quality assurance for textile fabrics generated from production lines is vital for competitive advantage. The computer vision-based automated inspection of textile fabrics has invited significant attention from researchers to develop effective techniques for fabric defect detection and classification. In this chapter we provide an overview of the open problems, the state-of-the-art on fabric defect detection and classification techniques, and also the promises of the new technologies that could make low-cost robust defect detection a reality for textile industries. This chapter also provides a summary of the research efforts for the automated classification of dynamically populated fabric defects. Finally we discuss the evolving new technologies which promise to significantly enhance the state-of-the-art in fabric defect analysis for industrial usage.

Key words: fabric defect detection, textile inspection, fabric defect classification, quality assurance.

3.1 Introduction

Automated quality assurance for textile fabric materials and products is one of the most challenging computer vision problems in real-world applications. The random variations in the knitting process, quality of fabric yarn, production and operating conditions often result in dynamically populated defects that vary in size, shape, appearance and color. The economic benefits resulting from the visual inspection for textile product quality are huge and justify the investment in automated computer vision-based solutions for product quality assurance. It is estimated that even the most highly trained inspectors can detect only about 70% of fabric defects, and that fabric defects reduce the value of produced fabrics by about 45–65% [41]. Recently some commercially available fabric inspection machines have entered the market. However, their cost is significantly high and the ranges of defects that can be detected are quite limited. The increasing availability of low-cost high-speed computers, high-resolution digital cameras and low-cost storage has generated much promise for robust automated textile inspection solutions to become popular in the near future.

3.2 Fabric inspection for quality assurance

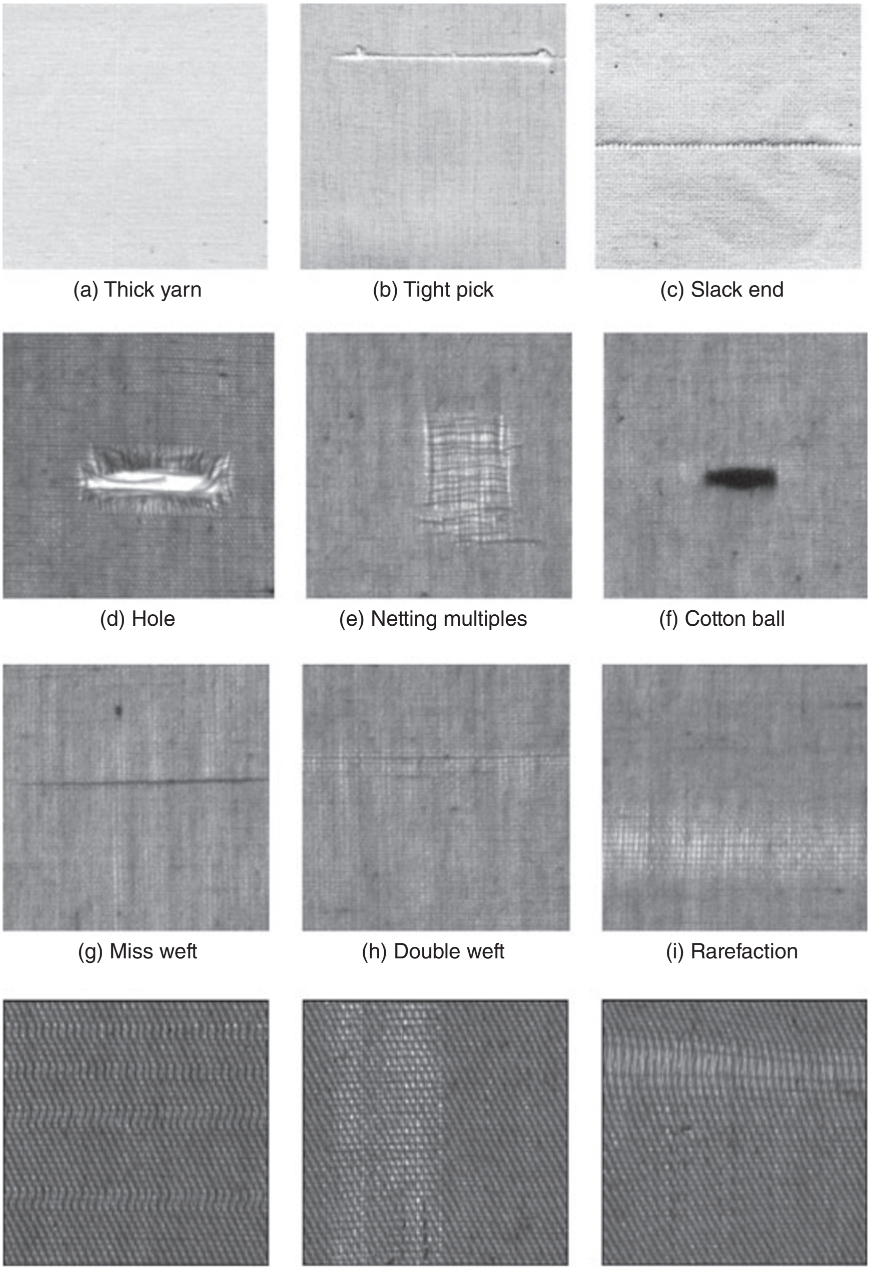
The inspection of textile fabrics is traditionally performed by human inspectors who are specifically employed and trained for this task. While trained inspectors locate the fabric defects offline with their prior knowledge, their judgment is highly subjective and often influenced by expectations. The subjectivity, high cost, labor and fatigue associated with human fabric inspection can be alleviated by automated computer vision-based inspection. Such inspection can potentially achieve high speed, consistency, efficiency, low cost and more objective quality assurance of textile fabrics. There are several kinds of fabric defects which can also be corrected for their repetitive occurrence if detected early during the online inspection. Such defect correction from the *automated* adjustment of process parameters is highly desirable and helps to reduce waste.

The production lines in textile industries generate a variety of fabrics: apparel fabrics, tie cord, industrial fabrics, piece-dyed fabrics, finished fabrics, denim, upholstery fabrics, etc. The range of commonly occurring defects in each category of these fabrics is large and the same class of fabric defect can appear quite differently on the same or different fabrics. Therefore the algorithmic requirements for the fabric defect classification are highly constrained by challenges from large intra- and inter-class variations in the fabric defects. The appearance of some class of fabric defects is a very poor guide to their true nature, and reference [42] details the response of such defects for human inspectors using physiological methods.

3.2.1 Fabric defects

The textile industry produces a variety of fabrics, e.g. woven, knitted, bondage, braided, upholstery, etc., for civilian and industrial applications. Each of these fabrics is essentially composed of yarns, which can be simple or complex, and characterized by their strength, twist and density. The woven fabric defects have been largely categorized into yarn defects and weave defects. Figure 3.1 illustrates nine different types of common defects on plain weave fabric samples and three on twill weave samples which are visible for low-resolution imaging. The photographs of the samples shown in Fig. 3.1(a)–(c) were acquired using front lighting, while those in Fig. 3.1(d)–(l) were acquired using back lighting. It may be noted that some defects (e.g. *start marks*) can be better observed in transmitted light while others (e.g. *oil spots*) can be seen more clearly in reflected lighting.

These defects can be generally categorized into horizontal, vertical and block types of weaving defects. Due to the nature of the weaving process, the majority of fabric defects are likely to appear in the vertical and/or horizontal directions. Some defects can be quite ambiguous, such as (e) and



(a) Thick yarn (b) Tight pick (c) Slack end

(d) Hole (e) Netting multiples (f) Cotton ball

(g) Miss weft (h) Double weft (i) Rarefaction

(j) Mispick (k) Netting multiples (l) Thin bar

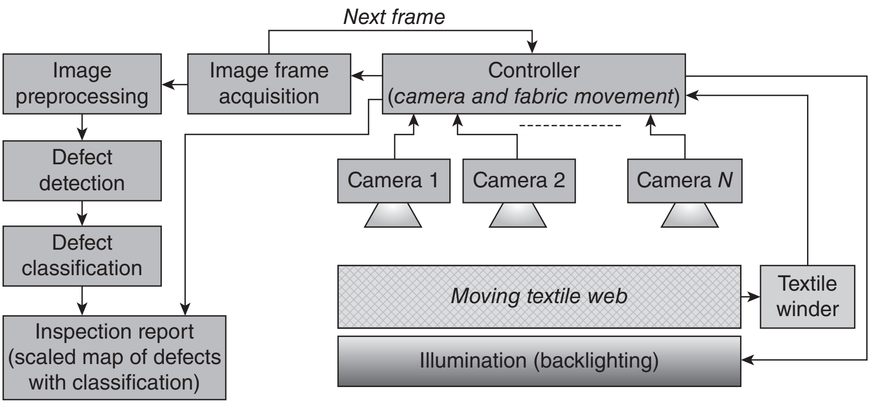
3.1 Image samples from common fabric defects in plain weave fabric (a)–(i) and twill weave fabric (j)–(l).

3.2 Image samples from fabric defects in patterned fabrics.

(f). They seem to have no exact distinction simply from color or shape. Therefore the classification of several categories of such defects can be highly subjective even for human inspectors. There are several established standards which provide details on the classes of fabric defects and help to impart more objectivity in the categorization of fabric defects, e.g., *Manual of Standard Fabric Defects in the Textile Industry* [38]. Figure 3.2 illustrates samples of patterned (textured) image samples acquired using high-resolution imaging (200 pixels per inch). The current state-of-the-art in textile inspection is more mature for the detection of plain/twill weave fabrics (Fig. 3.1) and the defect detection algorithms can detect the most popular defects with high accuracy. However, the detection of patterned fabric defects (Fig. 3.2) is quite challenging and is inviting a lot of research interest in developing effective defect detection approaches.

3.2.2 Automation for fabric inspection

The automated inspection of the textile web is often performed offline primarily for two reasons: the slow speed of the textile web from the production lines and the unfavorable environment because of excessive noise and fiber heap. On the other hand, online fabric inspection can be more suitable for high-resolution imaging and inspection as the slow speed of the moving fabric can allow complex computations on high-resolution images. Another advantage of online inspection is related to the possibility of online defect correction, i.e., some class of fabric defects (e.g. running warp defects, recurring filling defects) can be eliminated by correction of weaving parameters. The automation requirements for high-speed textile web inspection are summarized in Fig. 3.3. As shown in this figure, an array of digital cameras is synchronized with the fabric movement and covers the entire area of the moving fabric. Each of the acquired image frames is analyzed for the defect and the identified defects (if any) are classified into one of the many known fabric classes. The scaled map of the textile web is marked with the location and type of defects and used for grading/segmenting the quality of the fabric at different locations on the web.



3.3 Automation for quality assurance using computer vision-based inspection.

There are several commercially available solutions [46] for automated fabric defect detection and classification. The IQ-TEX system from Elbit Vision Systems [43], Fabriscan from Zellweger Uster [44] and Cyclops from BarcoVision [45] are some popular examples of such solutions. IQ-TEX and Fabriscan inspect the textile web offline or at the exit end of the inspection machine. Cyclops contains a traveling scanning head which can be deployed on the weaving machine itself for online inspection as it is generated from the weaving machine. The weaving process is therefore automatically stopped if online inspection detects any running or serious defects. These systems are designed to perform high speed, offline, fabric defect detection and classification. The high cost and limitations on the range of detected fabric defects have limited the large-scale deployments of currently available commercial solutions in the textile industries. There are also several efforts to develop (low-cost) fabric inspection solutions, using fuzzy wavelets and fractal scanning of fabric [47], multiscale wavelet decomposition [51] and Markov random field models [14, 49]. These efforts have attracted a lot of attention and continue to drive further research efforts to develop robust, low-cost and effective solutions for textile inspection.

3.3 Fabric defect detection methods

Most of the research efforts in the literature of fabric inspection have been focused on the detection of fabric defects. Reference [1] provides an extensive summary of fabric defect detection approaches, their limitations and advantages, presented in the literature (up to 2005). Table 3.1 summarizes some of the best-performing approaches for fabric defect inspection. The fabric defect detection approaches that can analyze the information from

Table 3.1 Best-performing approaches for plain and twill fabric inspection

Feature extraction	Reference	Comments
Gabor filters	[48]	Spatial and spatial-frequency domain local features
Wavelets	[47]	Wavelet analysis of 1D data from fractal scanning
Regularity	[50]	Texture similarity using localized regularity
Optimal filters	[52]	Linear finite impulse response filters

local regions have shown the most promising results in the literature. The fabric defect detection approaches that perform global analysis of the gray levels in the acquired image frames are more suitable for the detection of coarse defects. However, such appearance-based approaches can also be used to extract localized feature details, e.g. using kernel PCA, kernel LDA, etc., but have yet to be investigated in the literature. The localized extraction of information in the spatial and spatial-frequency domain has been shown to offer the best overall experimental results. Such localized feature extraction approaches, e.g. Gabor filters [48], wavelets [47], optimal filters [52], etc., are highly suitable for online fabric inspection. In addition, localized feature extraction using texture regularity [50] has been shown to offer the most promising results on the publicly available TILDA database and is highly effective for detecting defects from complex texture backgrounds.

Another localized feature extraction approach recently presented in the literature uses localized binary patterns (LBP) for the feature extraction. Such an approach effectively extracts phase information from the localized window regions to characterize the textile image. Tajeripour *et al*. [28] demonstrated that the LBP phase features showed promise in detecting fabric defects in patterned fabrics. These authors applied LBP masks to the local windows of each fabric image, and this LBP feature from a sub-window containing defects was compared with that of the reference image (normal fabric) to determine whether a defect can exist.

Mak *et al*. [29] presented another promising approach for fabric defect detection using local texture analysis based on morphological operators. The authors used a Gabor wavelet network (GWN) for the extraction of localized texture features from the defect-free fabric images. The GWN is constructed from the imaginary Gabor wavelets and used to construct a structuring element for morphological filters. Finally, the authors employed a few such tuned morphological filters and illustrated promising defect detection results on 32 commonly appearing textile defects on twill, plain and denim fabrics. One of the notable advantages of this approach lies in its smaller computational complexity resulting from the tuned morphological operators, which makes it an attractive choice for online textile inspection.

3.3.1 Fabric defect detection in patterned fabrics

The detection of defects in patterned fabrics is quite challenging and is inviting increasing interest among researchers. The patterns of textures in textile fabrics can be more effectively analyzed from the spatial arrangement of gray levels. We can consider patterned fabrics as being constructed from the repetition of a unit pattern [7]. The analysis of such textures involves four key steps [31]: texture segmentation, texture classification, texture synthesis and shape studies. Some properties such as uniformity, coarseness, roughness, directionality, regularity, etc., have been widely studied in the texture segmentation literature. Among these properties, regularity analysis of patterned textures has received growing attention, which is an important feature because it is an invariant but perceptually motivated feature. Ngan and Pang [32] also used the wide existing regularity in textured images and proposed an approach they called the regular bands method, which is based on the idea of periodicity. The key idea of the regularity approach is to study or represent signal generation for each vertical and horizontal line of the defect-free region. Any defect in a defective region would correspond to an irregularity in the signal.

Kuo *et al.* [30] developed an automated visual inspection approach, based on wavelet transform (WT), for the detection of defects on a patterned fabric. Wavelet transform had been successfully applied earlier [47, 51] for the detection and classification of defects on plain fabrics. The authors compared three methods on the WT decomposed sub-images and showed that the method of wavelet pre-processed golden image subtraction (WGIS) has the best rate, which is up to 96.7%. Actually, this method is the combination of WT and the technique of golden image subtraction (GIS). WT is used as a tool to reduce the noise in the texture image, which is a key problem in defect detection. Then GIS is applied to the WT decomposed image. In this process, the authors acquired the golden image, which is bigger than the pattern unit in the textures from a reference image. Then, for every test image, this golden image moves over and the energy measure is computed for each pixel. The thresholding of the entropy values for each pixel determines the location of defects in the textured test images.

Defect detection on patterned textures using hash functions has been investigated by Baykal *et al.* [39]. Hash functions were originally used in cryptography to ensure integrity of files. A family of special hash functions was developed in this work. The authors applied these functions to textured images in the horizontal and vertical directions respectively. The location of defects in the texture image can be ascertained by thresholding the output from the two directions. These functions were shown to be quite effective and sensitive for defect detection in the texture. The key motivation for using this approach is that the hash functions are immune to variations in illumination and contrast.

3.4 Fabric defect classification

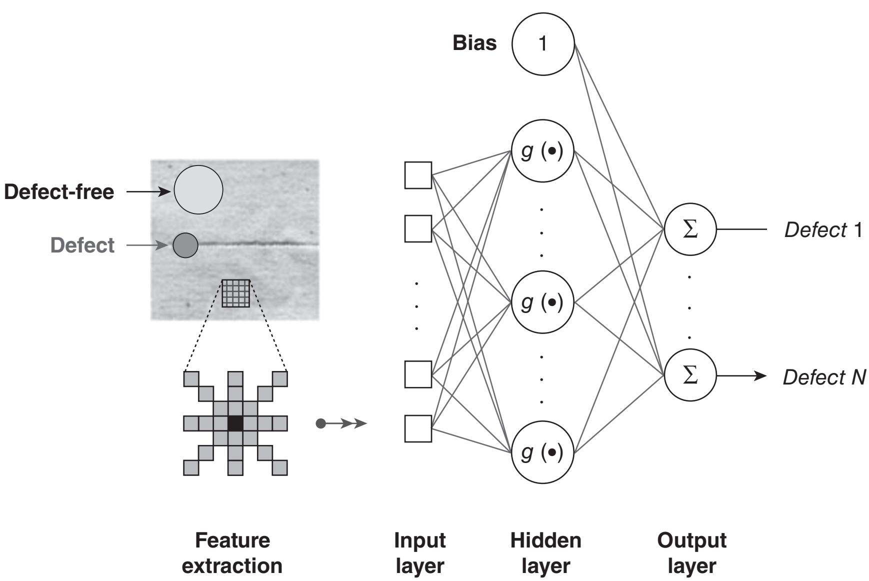
Most of the literature on automated textile inspection is predominantly focused on the detection of fabric defects [1–6, 8, 15] and little attention has been paid to the automated classification of localized or detected defects. Automated fabric defect detection is required to automatically segment defect-free fabric from fabric with defects and precisely compute the location of defects on the moving textile web. The classification of such localized defects into one of the several known categories is necessary to further ensure quality assurance and for the economic usage of the textile product. Some of the detected fabric defects are severe and accordingly have to be eliminated (trimmed) from their localized position on the textile web. However, some defects can be very subtle, i.e., least severe, and result in lowering the quality of fabric for its economic usage. In summary, fabric defect detection is required to ensure freedom from defects and a high level of quality assurance, while the classification of such detected defects is required for the economic usage of products and for the defect analysis to reduce or eliminate the occurrence of such defects.

Fabric defect classification is largely treated as a popular pattern classification problem and therefore researchers prefer to use mature machine learning approaches for defect classification [9–12]. The supervised pattern classification methods require categorization of multiple classes of detected or presented fabric defects into one of the possible patterns in the training database. Due to the large number of fabric defect classes, large intra-class and small inter-class variations, the selection of training samples and classes largely determines the upper limit to the achievable performance. There has been no effort, to the best of our knowledge, by researchers to train the classifier for more than 100 classes of fabric defects and to carry out the performance analysis. Plausible reasons for this could be the absence of such a large database and/or the large inter-class similarity of fabric defect classes, which is likely to present less discriminating (or more confusing) samples for effective training. Several fabric defects look quite similar (or the same) while belonging to different defect classes, and several defect classes may appear differently at different locations or frequencies on the textile web. A rigorous comparative experimental evaluation of the performance for the fabric defect classification on a very large number of defect classes, from several machine learning approaches, has not yet been attempted and would be of high interest for system development.

The entire process of fabric defect classification largely consists of three stages: feature extraction, feature analysis and training the classifier. For the classification task, it has to be ensured that enough representative fabric defect samples are available. These samples are used for training the classifier. The classifier can then learn to discriminate among those defects of known class using the discriminant features. Therefore the selection of feature representation scheme is equally important in achieving accurate defect classification. The classifier learning process depends greatly on the training samples, the feature representation, the training algorithm and the parameters of the training process. The most promising fabric defect classification results have been achieved from the neural network (NN) and support vector machine (SVM) based classifiers. Such learned classifiers often have little complexity and therefore are highly suitable for online classification of fabric defects. We now briefly discuss these classifiers.

3.4.1 Neural network-based fabric defect classification

A simplified structure of a neural network with one hidden layer is shown in Fig. 3.4. The two-layer structure illustrated here could be the simplest one, which includes an input layer and an output layers. The more complex



3.4 Structure of a neural network with one hidden layer.

structure, often required for the effective classification of large classes of fabric defects, additionally has one or more hidden layers between the input and output layers. A neural network with a two-layer structure is too simple and lacks generalization capability for the classification problem. Therefore we prefer to use three-layer neural networks, which contain one hidden layer, and can provide more effective classification capability from representative feature vectors. Each layer has several nodes which play different roles. The nodes in the input layer connect to the real world, where the discriminant features extracted from the unknown or input image are made available. The number of these nodes highly depends on the number of the dimension of feature vectors. The number of the output nodes is related to the nature of the classification problem. Each node can be seen as a class output from neural networks, which means that if the value of this node is the maximum, then the unknown input image or defect can be classified in its corresponding class. The exact number of the nodes in the hidden layer is a critical parameter which highly affects the generalization capability of the neural network. Empirically, it can be estimated from the number of input and output nodes. If N_{i}, N_{h} and N_{o} represent the number of input, hidden and output nodes respectively, then they are related by $N_{\mathrm{h}} = \sqrt{N_{\mathrm{i}} N_{\mathrm{o}}}$. This is a popular rule of thumb and provides a reasonable estimate to determine the number of nodes. The values of the nodes in the hidden layer and the output layer are related as follows:

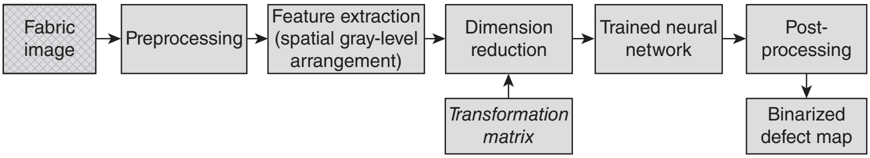
$$\varphi_j^l = \sum_{i=1}^{N_{l-1}} w_{ij}^{l-1,l} y_i^{l-1} \qquad 3.1$$

$$y_j^l = g(\varphi_j^l) \qquad 3.2$$

where the sum of weighted inputs for the jth ($j = 1, \ldots, N_{l-1}$) neuron in the lth layer is represented by φ_j^l. The weights from the ith neuron at the $(l-1)$ th layer to the jth neuron in the lth layer are denoted by $w_{ij}^{l-1,l}$ and y_i^l is the output for jth neuron in the lth layer. The popular practice is to provide the values of −1 and 1, corresponding to 'defect' and 'defect-free' responses, to the network during training as the correct output responses expected for the two-class classification (pixel gray-level values) from the training.

Reference [16] uses a two-layer network with a hyperbolic tangent sigmoid activation function for learning the local arrangement of gray levels to detect fabric defects. Back-propagation (BP) is used to minimize the training error between the output and the expectation. In this iteration process [16], the BP algorithm adjusts the weights between layers automatically. Such a trained neural network can be well adapted for the two-class fabric classification problem.

The approach detailed in [16] uses the feature vector formed by the gray-level values of neighboring pixels for training the neural networks. The trained network successfully segments the defects from the fabric under



3.5 Flow diagram of fabric defect segmentation using neural network.

Table 3.2 Classification accuracy of neural network classifier for five leather defects

	Line	Stain	Hole	Knot	Wear	Total
Accuracy (%)	100	100	95	100	90	96.25

inspection and generates a binarized defect map as illustrated in Fig. 3.5. In this method, principal component analysis (PCA) has been applied to feature vectors to reduce the dimension of the feature vector. The experimental results suggest that this method is robust for the segmentation of 11 different fabric defects, including twill weave fabric and plain fabric samples. The work detailed in [16] is quite effective and details the effectiveness of a neural network in learning the gray-level arrangement in a fabric structure to find defects. However, the key purpose of our discussion, to detail fabric defect classification, has not been attempted in [16]. The classification of detected defects into one of the known defect categories has, however, been attempted in the literature for quality assurance applications with promising success. Kwak *et al.* [17] employed a multi-layered neural network to classify five different types of leather defects: lines, holes, stains, wears and knots. They extracted geometrical information from the localization of defects detected through the local thresholding and morphological operations. In the experiment, the authors used 140 image samples with defects, 60 of which were employed for the training (12 for each class) with the other 80 used for the test (10 for each of line and hole, 20 for each of the other three). The trained neural network with a single hidden layer was used for the defect classification and the results are summarized in Table 3.2. The authors showed that the neural network can achieve better classification accuracy than when a decision tree is employed for the classification.

Liu *et al.* [18] used a PSO-BP (Particle Swarm Optimization – Back Propagation) neural network with orthogonal wavelet transform as the feature for the classification of fabric defects. In this work [19], the authors attempted to alleviate two key problems with the use of a neural network: large training complexity and local minimum. The strategy is to use PSO

Table 3.3 Classification accuracy of neural network classifier for five stitching fabric defects

	Pleats	Puckers	Tension	Skipped-stitches	Holes
Accuracy	100	100	100	100	93

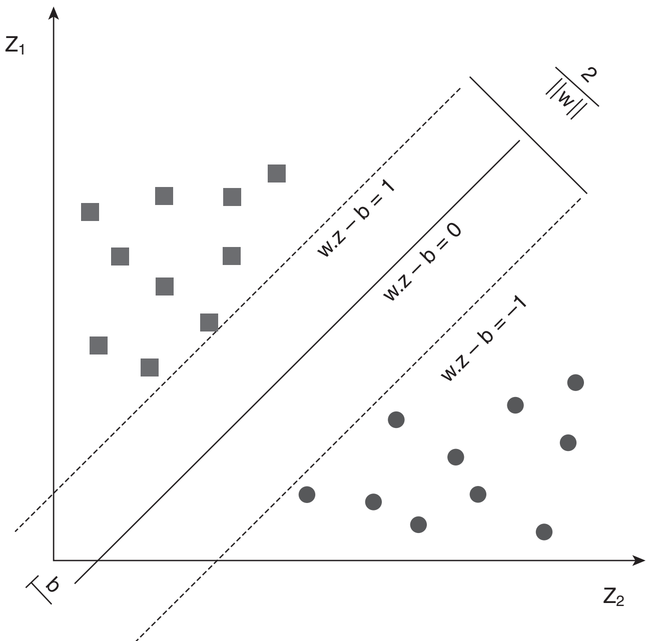
for the global optimization with a high search speed to achieve more effective optimization in a given time. The authors evaluated this approach on the classification of five different types of fabric defects: warp direction defect, weft direction defect, particle defect, hole and oil stain defect. They claimed to have achieved better performance than the BP neural network from the output of the classifier, and to shorten the training time and complexity simultaneously.

The classification and detection of stitching fabric defects using wavelet decomposition and neural networks has been investigated by Wong *et al.* in [13]. The classification results achieved in this paper demonstrate that the proposed method can identify five classes of stitching defects effectively. The five stitching defects are pleats, puckers, tension, skipped-stitches and holes. Table 3.3 summarizes the classification accuracy achieved in [13].

Kuo *et al.* [30] have also illustrated the classification of fabric defects using 1×4096 line scan camera imaging. This is a simplified approach that uses projective summation of fabric image gray levels for the neural network-based classification. The authors claimed to have achieved classification accuracy of 90% for weft-lacking and warp-lacking fabric defects, while oil stains were more effectively identified with an accuracy of 95%.

3.4.2 Support vector machine (SVM)-based fabric defect classification

In statistical learning theory, SVM is the representative of a set of methods referred to as kernel methods. In this approach, the SVM estimates the required support vectors from the training samples. In the two-class case (Fig. 3.6), these support vectors are the points from which two parallel lines pass to discriminate the feature points of the two classes and also have the maximum distance between them. However, not all the features from different classes are well separated in practice. In order to eliminate the overlap among them, features are first projected into a space with higher dimension through a nonlinear transform. In this new space, features tend to be more effectively separated from those of different classes. In this process, the inner product of new features will be computed, which can instead be solved in the initial space using a nonlinear function. There are



3.6 Estimation of decision boundary for a two-class SVM.

several choices for the nonlinear functions: Gaussian, polynomial, tan-hyperbolic function, etc. The decision surface using the Gaussian function is estimated as follows:

$$f(x) = \operatorname{sgn}\left\{\sum_{i=1}^{N} w_i \exp\left(-\frac{\|x - x_i\|^2}{c_i}\right) + b\right\} \qquad 3.3$$

where c_i and b are constants, and x_i is the centers of support vectors.

Hou and Parker [20] investigated a promising approach for texture defect detection using SVM and Gabor features. In this paper, the authors adopted the one-against-all strategy for a binary SVM classifier to discriminate between defective and non-defective pixels. They selected 50 images from a Brodatz texture album [21] and the classification accuracy for the two cases is summarized in Table 3.4.

Kumar and Shen [22] used SVM and gray-level values of neighboring pixels as the feature to inspect fabric defects. A polynomial kernel of order 3 was employed in the SVM. This work details comparison between the SVM and the neural network performance for fabric inspection. The results in [22] suggest that the two schemes are both computationally similar for the inspection but SVM does not suffer from the problem of a local minimum and is computationally simple to train. Kim *et al*. [23] investigated

Table 3.4 Classification accuracy from two different cases (%)

Texture images	Proportion of training data (%)	Full Gabor filters	Optimal Gabor filters
D77 vs others	2	92.37	87.36
	4	92.57	87.31
	6	92.66	87.39
D4 vs others	2	81.01	77.84
	4	81.75	77.92
	6	84.99	78.09

Table 3.5 Summary of related defect classification methods from the literature

Reference	Year	Classifier	Database	Fabric quality	Accuracy (%)
[20]	2002	ANN	2 (defect-free and with-defect)	Plain and twill	NA
[21]	2000	ANN	5	Leather	96.25
[22]	2008	ANN	5	Plain	NA
[24]	2009	ANN	5	Stitching defect	98.6
[25]	2005	SVM	2 (positive and negative)	Brodatz texture	92.66 (best)
[27]	2002	SVM	2 (defect-free and with-defect)	Plain and twill	NA
[28]	2002	SVM	2 (positive and negative)	Brodatz texture	83.9 (best)
[30]	2006	GMM	12	Brodatz texture	99.61
[31]	2009	GMM	9	Plain	85
[32]	2003	K-NN	21491 (15 defect classes)	Wood surface (parquet slabs)	91.4% (best)

texture classification using SVM rigorously on several image databases including a Brodatz album [21] and an MIT vision texture database [24]. The gray-level values of neighboring pixels were used as the feature for classification. Different kernel functions and different multi-classification schemes for SVM were compared in this work. On the multi-texture images (four Brodatz textures), the authors achieved the best error rate of 16.1% when a 17×17 median filter was employed for the post-processing.

Although neural networks and SVM have emerged as the most promising classifiers for fabric defect classification (refer to Table 3.5), some other classifiers have also been investigated for texture classification. Kim and Kang [25] used a Gaussian mixture model (GMM) and a wavelet packet frame to extract texture features. The texture features from each class are evaluated by GMM and observed to be quite distinct from each other. In the test phase, the features extracted from each of the unknown images are employed to estimate the probability and find the model with maximum likelihood. The class of maximum probability model is assigned to the unknown test image. For 12 different textures from a Brodatz album [21], the authors achieved a classification accuracy of 99.61%.

Zhang *et al*. [26] have used GMM and Gabor filters to effectively demonstrate fabric defect classification. The Gabor-filtered responses from each of the fabric images are statistically quantified to extract feature vectors. The mean and covariance of these responses are used to estimate the model parameters for each GMM. The key advantage of GMM is that it can approximate any unknown distribution in a weighted sum of several multivariance Gaussian distributions with different parameters. Therefore the GMM can be effectively used to characterize the distribution of features from the different fabric defects. The GMM is derived using an expectation maximum (EM) criterion. Generally the number for GMM has to be estimated first. However, the precision of the estimated model highly influences the performance. Zhang *et al*. [26] also employed the minimum description length (MDL) estimator to estimate the appropriate model order for each of the GMMs. They illustrated experimental results for the nine fabric defect classes and achieved an average classification accuracy of more than 85%, which is a little better than SVM in their work.

Mäenpää *et al*. [56] presented one of the most promising efforts for the inspection of wooden surface images that employed a large number of test samples for evaluation on 15 different classes of defects. They explored a variety of features and developed a methodology for combining color and texture features. They achieved their best results, i.e., an error rate of 8.6%, using signed differences quantized with 128 code vectors along with LBP features. The experimental results indicate that such an approach is likely to achieve high performance if attempted for the classification of fabric defects.

3.5 Fabric properties and color measurement using image analysis

Computer vision-based analysis of fabric samples is not limited to quality assurance but is increasingly employed for the objective/automated assessment of color, pattern and physical measurement [27, 40]. The manual measurement of fabric density, i.e., number of warp and weft yarns per unit distance, is time consuming and prone to errors. Therefore computer vision-based analysis of fabric images to automatically compute the actual fabric density has been developed. The Fourier spectra of the acquired (high resolution) fabric image can be used to ascertain warp and weft yarn density. Escofet *et al*. [54] have used such spectral domain energy analysis to identify fabric structure in the spatial domain. However, such an approach is not suitable for patterned fabrics as the periodicity of patterns, rather than individual yarns, appears in the combined power spectrum. The gray-level co-occurrence matrix-based fabric image analysis is more complex but has been attempted in [36] with little success. Jeong and Jang [34] and Kuo *et al*. [37] proposed fabric density measurement using measurements of the gray-level fabric profile. The experimental results in these efforts are promising and illustrate success on plain and patterned fabrics. The fabric image analysis can also be used to automate the measurements of yarn thickness and weave characteristics of underlying fabric.

The weave patterns for double-layer weft woven (necktie) fabric can also be ascertained from the autocorrelation analysis of the fabric image [53]. However, the common necktie patterns are complicated and this algorithm cannot work for complex fabrics of more than double-layer or even special single-layer weaves. Woven fabrics can also be geometrically modeled to describe their structure. The identification of fabric weave patterns using such *active grid models* that can contain their geometrical, structural and color details with a high success rate is proposed in Xin *et al*. [55]. Another emerging application of fabric image analysis is for fabric color analysis, i.e., color density, color composition, etc. Pan *et al*. [33] present fabric color analysis using a fuzzy clustering algorithm. The comparative fabric color analysis using a chromatography, spectroscopy and mass spectrometry has a range of applications in criminal investigation. The forensic analysis of textile fabrics is primarily employed to trace the materials that can identify the suspects, victims and crime scenes to scientifically establish the contact between individuals and objects. For example, visible microspectrophotometry can effectively distinguish between colored fibers, which may appear to be visually similar, from their spectral characteristics. There has been a significant amount of research into the forensic analysis of dyed textile fibers using mathematical analysis of spectroscopic data, and reference [35] summarizes these efforts.

3.6 Conclusions and future trends

Computer vision-based textile inspection is inviting a lot of interest, primarily for the objective assessment of textile quality and non-destructive measurements of the physical properties. The majority of research efforts in the literature [41] have evaluated fabric quality assessment on either plain or twill fabrics. The defects in such fabrics have a comparatively clear background texture to distinguish from the defect-free regions. Therefore the defect inspection approaches tested on such uniform colored and textured fabrics have very limited applications for the textile industry. Most of the textile fabric products for consumer use are colored and patterned. Such fabrics have complex patterns which are quite challenging for defect inspection and present a common limitation for the popular fabric defect detection approaches. Therefore the next generation of textile inspection approaches should effectively be able to detect defects from the complex patterns on the moving textile web. Such capabilities use scale, translation and rotation invariance techniques to match given regular pattern(s) whose repetition can be random rather than uniform. Research efforts should therefore be focused on the use of advanced feature extraction and matching techniques which can offer scale, translation and rotation invariant capabilities. Secondly, a higher level of imaging setups should be explored, since the textile fabric is a 3D surface. The 3D imaging of a textile surface can allow us to detect defects which are not visible using conventional imaging. Such an approach can therefore ensure a higher level of quality assurance and therefore should be pursued for the next generation of textile fabric inspection systems. The classification of fabric defects using a novel neural network based on the principle of *Autonomous Mental Development* (AMD) [57, 58] can be a promising tool for addressing the problem of dynamic defect populations that has not yet attracted attention from researchers. The AMD detector can be judiciously designed to autonomously develop its classification skills according to its learning environment during the online fabric inspection.

It is widely expected that sensing, storage and computational capabilities of automated computer vision-based fabric inspection systems will continue to improve. The development of smart sensing technologies will allow researchers to effectively exploit extended fabric features, i.e. structure, texture and color, and develop high-performance feature extractors. While this will significantly improve the throughput and usability, there are still some fundamental issues related to the representation of complex structured (patterned) fabrics, robust defect detection, and accurate classification of dynamically populated fabric defects. Therefore, future textile inspection systems must overcome many hurdles and challenges to meet a wide range of application requirements for the textile industry at low cost.

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