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Review article

Automated fabric defect detection—A review☆

Henry Y.T. Ngan [a,*], Grantham K.H. Pang [a], Nelson H.C. Yung [b]

[a] Industrial Automation Research Laboratory, Department of Electrical and Electronic Engineering, The University of Hong Kong, Pokfulam Road, Hong Kong
[b] Laboratory for Intelligent Transportation System Research, Department of Electrical and Electronic Engineering, The University of Hong Kong, Pokfulam Road, Hong Kong

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ABSTRACT

This paper provides a review of automated fabric defect detection methods developed in recent years. Fabric defect detection, as a popular topic in automation, is a necessary and essential step of quality control in the textile manufacturing industry. In categorizing these methods broadly, a major group is regarded as non-motif-based while a minor group is treated as motif-based. Non-motif-based approaches are conventional, whereas the motif-based approach is novel in utilizing motif as a basic manipulation unit. Compared with previously published review papers on fabric inspection, this paper firstly offers an up-to-date survey of different defect detection methods and describes their characteristics, strengths and weaknesses. Secondly, it employs a wider classification of methods and divides them into seven approaches (statistical, spectral, model-based, learning, structural, hybrid, and motif-based) and performs a comparative study across these methods. Thirdly, it also presents a qualitative analysis accompanied by results, including detection success rate for every method it has reviewed. Lastly, insights, synergy and future research directions are discussed. This paper shall benefit researchers and practitioners alike in image processing and computer vision fields in understanding the characteristics of the different defect detection approaches.

Contents

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* Corresponding author. Tel.: +852 2859 2689; fax: +852 2559 8738.
E-mail addresses: ngan.henry@gmail.com (H.Y.T. Ngan), gpang@eee.hku.hk (G.K.H. Pang), nyung@eee.hku.hk (N.H.C. Yung).

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1. Introduction

Fabric, being a widely used material in daily life, is manufactured with textile fibers. Textile fibers can be made of natural element such as cotton or wool; or a composite of different elements such as wool and nylon or polyester. A defect means a flaw on the fabric surface, as a result of the manufacturing process. In automation, fabric defect detection (also called inspection) is a quality control process aimed at identifying and locating defects. Traditionally, human inspection, carried out in wooden board, is the only means to assure quality. It helps instant correction of small defects, but human error occurs due to fatigue, and fine defects are often undetected. Hence, automated inspection becomes a natural way forward to improve fabric quality and reduce labor costs. However, the task is challenging to say the least. At present, there are more than 70 categories of fabric defects [1] defined by the textile industry. A typical state-of-the-art automated fabric inspection (Fig. 1(a)) achieves a success rate of higher than 90% (Fig. 1(b)) as compared with 60–75% by human [2].

Fabric can be considered as two-dimensional (2D) patterned texture. In general, not all 2D textures, such as natural scene images, are designed with patterns. A 2D patterned texture is defined by an underlying lattice with its symmetry properties governed by 17 wallpaper groups [3,4]. In mathematical algebra, the wallpaper groups also known as the crystallographic groups are well-defined. As such, patterned texture of a particular group can be generated by at least one of the symmetry rules on lattice among translational, rotational, reflectional and glide-reflectional symmetries (Fig. 2). These 17 groups are named as p1, p2, pm, pg, cm, pmm, pmg, pgg, cmm, p4, p4m, p4g, p3, p3m1, p31m, p6 and p6m, where letter p refers to a primitive while c is a face-centered cell. The integer that follows p or c denotes the highest order of rotational symmetry that is 1-fold, 2-fold, 3-fold, 4-fold or 6-fold. Symbol m indicates a reflectional symmetry whereas symbol g refers to glide-reflectional symmetry. A glide-reflectional symmetry means that a pattern can reflect in one line and translate along a certain distance, intending to get exactly the same pattern. Various patterned textures [5–8] can be found on surfaces of materials such as fabrics (textile products), wallpaper, ornaments, tile, vase, and paintings. In essence, the production method determines which wallpaper group the fabric belongs. For example, plain weave fabric (Fig. 3(a)) [9,10], and knitted fabric (Fig. 3(b)) [11,12] are produced by weaving and knitting, respectively; twill fabric (Fig. 3(c)) [13–15] is produced by either weaving or printing; laces (Fig. 3(d)) [16,17] are produced by knitting and carpets (Fig. 3(e)) [18,19] are produced by either weaving, printing or spinning.

In particular, defects [1] result from machine faults, yarn problems, poor finishing, excessive stretching, among others. Six common defects are shown in Fig. 4. Gout (Fig. 4(a)) is a lumpy and asymmetrical fault in a spun yarn of a fabric which occurs during spinning, warp float (Fig. 4(b)) is a length of yarn that is unbound over two or more successive ends or picks on the warp direction, and a drawback (Fig. 4(c)) is a weave distortion characterized by tight and slack places in the same warp yarn. Definitions of hole (Fig. 4(d)), dropped stitches (Fig. 4(e)) and press-off (Fig. 4(f)) can be read in [1]. A serious defect can render the fabric product unsalable and a loss in revenues, while a small defect can be corrected by skillful workers. Automated fabric inspection is therefore beneficial, yet there are challenges: (a) numerous categories of fabrics, (b) distinct composition of various wallpaper groups of fabric texture, and (c) similarity in shape between defects and background texture [20]. It is not easy to

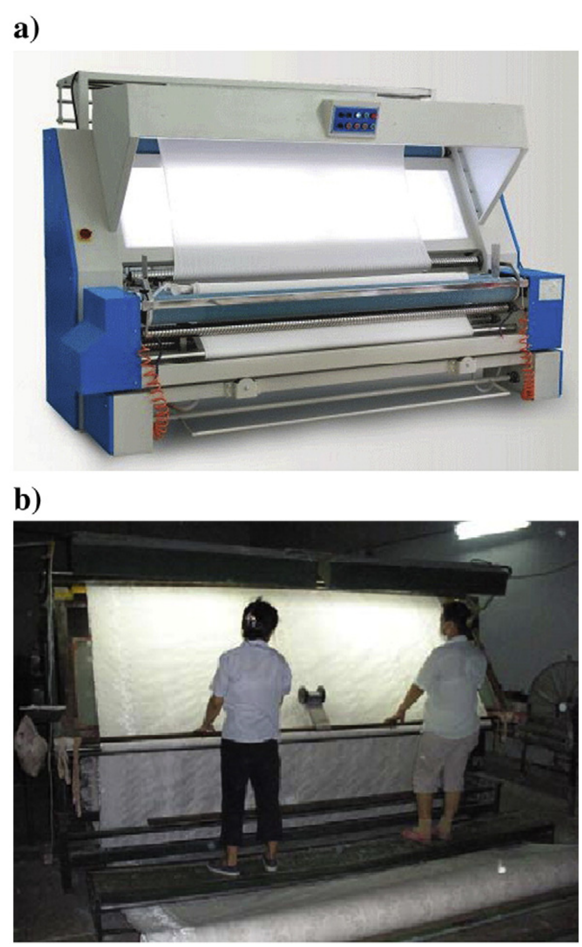

Fig. 1. (a) Machine automated inspection, and (b) manual inspection (picture captured in a Jacquard textile manufacturing factory in China).

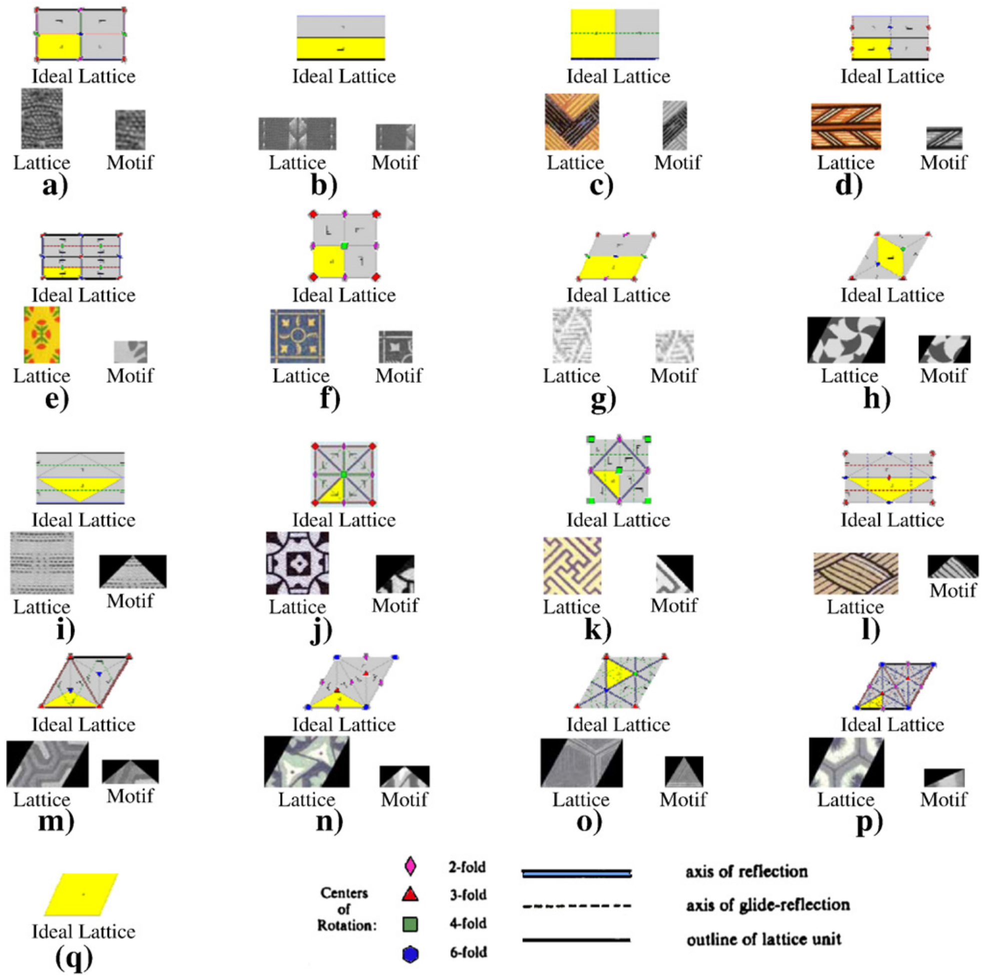

Fig. 2. Ideal lattices [5], lattices and motifs for 17 wallpaper groups: (a) pmm, (b) pm, (c) pg, (d) pmg, (e) cmm, (f) p4, (g) p2, (h) p3, (i) cm, (j) p4m, (k) p4g, (l) pgg, (m) p31m, (n) p6, (o) p3m1, (p) p6m, and (q) p1.

tackle all the challenges by a single method and hope to achieve high detection success rate for a large quantity of samples from various groups.

Fabric defect detection has been a popular research topic [21,22] for many years. Majority of papers is focused on what we called a non-motif-based approach, while a new approach which has been developed recently [3,8] considers motif as a basic manipulation unit, based on the wallpaper group definition. This new motif-based approach employs the characteristics of the smallest unit of a pattern, a motif, in the design of its methodology. Conversely, the non-motif-based approach utilizes more than one motif (usually with large number of motifs) to extract suitable features.

Broadly, these methods can be categorized as depicted in Fig. 5. The traditional non-motif-based methods can be further sub-divided into two categories: those that are used for the p1 wallpaper group, which is composed of one fundamental lattice with one motif only, and those for the other wallpaper groups. Its typical example is plain and twill fabric. Apart from those that can be defined by wallpaper groups, there are other textures that consist of random, non-directional components or a mixture of patterned and non-patterned materials namely printed circuit boards (PCBs) [21,23–25], wood [26–32], wafer [33], pearl [34], and rail [35].

Recently, Kumar [36] reviewed 166 papers for fabric inspection. Yet, a majority of his references was published before year 2000 (15.06% before 1990, 63.86% in 1991–2000). In contrast, this paper is most up-to-date with 52.52% of references (73 references) after 2001 (8.63% before 1990, 38.85% in 1991–2000). Methods of statistical approach (bi-level thresholding, gray-level statistics, edge detection, Eigen filters and rank-order functions), spectral approach (Wigner distribution) and model-based approach (Poisson's model) as reviewed in [36] are outdated and lack prominent results. Therefore, they are not considered in this paper. On the other hand, the new detection methods in statistical, spectral, model-based, learning, hybrid and motif-based approaches, which have promising results are presented. In summary, the main contributions of this paper are:

1. Recent research activities on fabric defect detection are summarized and their significant features are outlined. The pros and cons of each approach are also discussed.
2. It offers a wider categorization of methods of seven classes (i.e., statistical, spectral, model-based, learning, structural, hybrid, and motif-based).
3. It also provides a qualitative analysis for each chosen method. Detection success rate, quantity of samples for testing, and strengths and weaknesses for every method are listed and compared for method.

This paper is organized as follows. Section 2 describes the performance metric for defect detection. The non-motif-based methods of defect detection on the p1 group are depicted in Section 3. Those on other wallpaper groups (hybrid approach) are presented in Section 4. Section 5 delivers the motif-based method for 16 wallpaper groups. Section 6 offers a summary of this paper. Section 7 addresses the future direction and conclusions.

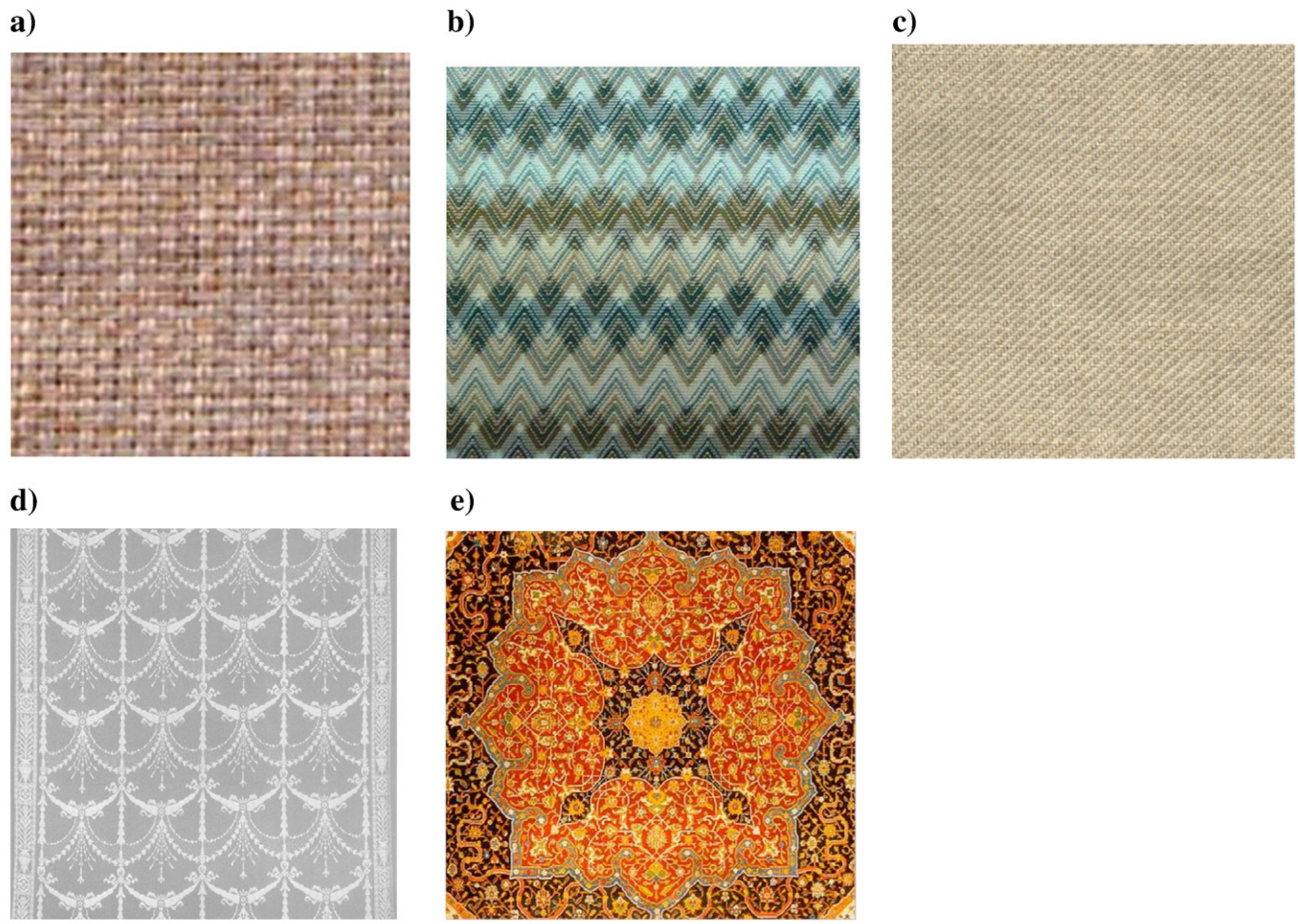

Fig. 3. (a) Plain weave fabric, (b) knitted silk fabric, (c) linen twill fabric (d) lace, and (e) carpet.

2. Performance metric for defect detection

There are two ways to measure the accuracy of detection, (a) *detection success rate* or (b) *sensitivity* and *specificity* [8]. Generally, *detection success rate*, also known as *detection accuracy*, is defined as

$$\textit{Detection Success Rate} = \frac{\textit{Number of Samples Correctly Detected}}{\textit{Total Number of Samples}}, \quad (1)$$

where samples include defective and defect-free samples, or it can be further defined as *detection rate* and *false alarm rate*. Their definitions are

$$\textit{Detection Rate} = \frac{\textit{Number of Defective Samples Correctly Detected}}{\textit{Total Number of Defective Samples}}, \quad (2)$$

$$\textit{False Alarm Rate} = \frac{\textit{Number of Defect-free Samples Detected as Defective}}{\textit{Total Number of Defect-free Samples}}. \quad (3)$$

Table 1 outlines definitions of *true positive (TP)*, *false positive (FP)*, *true negative (TN)*, *false negative (FN)* in defect detection. Alternatively, detection success rate can be defined as

$$\textit{Detection Success Rate} = \frac{TP + TN}{TP + FN + TN + FP}. \quad (4)$$

On the other hand, correct detection of defective samples (i.e. sensitivity) and correct detection of defect-free samples (i.e. specificity) can be defined as

$$\textit{Sensitivity} = \frac{TP}{TP + FN}, \quad (5)$$

$$\textit{Specificity} = \frac{TN}{TN + FP}. \quad (6)$$

As observed from real implementation of fabric inspection systems, it is necessary to consider factors such as (1) contrast between defects and texture surface [20,37]: e.g., a low contrast in image easily leads to a misclassification; (2) consistency of texture background [37]: e.g., color difference and distortion along a texture affect image acquisition; (3) resolution of input image [19,37–41]: e.g., a low resolution image cannot show fine defects in fabric; (4) alignment of input image [3,42,43]: e.g., misalignment in image acquisition induces false defect detection in template matching approach; (5) size [37,44], and shape [45–47] of defects: e.g., defect of small size or defect similar to a pattern shape increases difficulties in recognition; (6) speed or computation complexity of defect detection [37,48,49]: e.g., long learning delays may not be practical; (7) lighting [13]: e.g., improper illumination yields poor resolution and contrast; and (8) image acquisition techniques: e.g., most inspection methods use digital cameras to capture images. However, alternative approaches are also available, such as near-infrared (NIR) [50], X-ray, multispectral imaging and polarimetry, which may provide extra features in defect

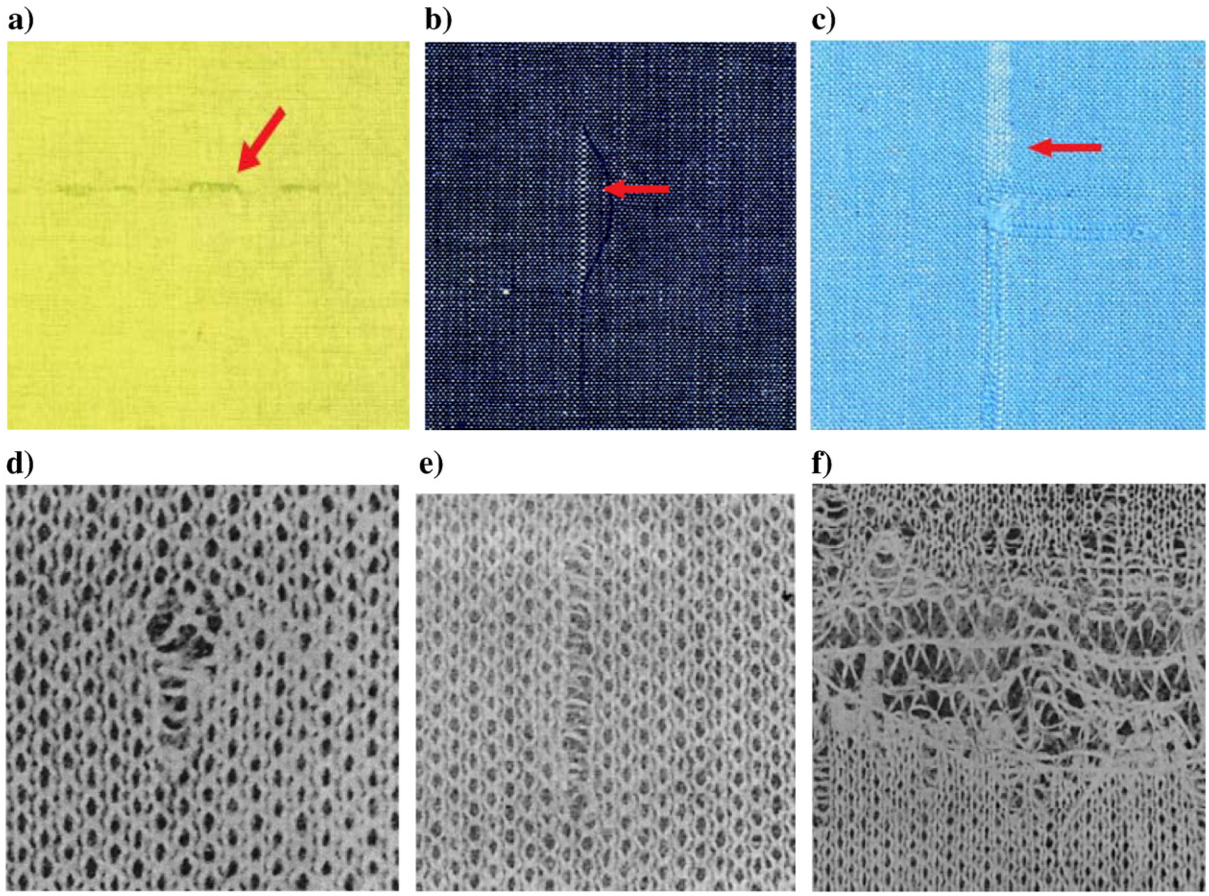

Fig. 4. Examples of defects [1] namely (a) gout, (b) warp float, (c) drawback, (d) hole, (e) dropped stitches, and (f) press-off. (Arrows point to defective regions.)

detection. Generally, there is always a trade-off between the different characteristics in the design of a defect detection method. There is no doubt that a proper assessment and balance of each characteristic would likely lead to a more satisfactory detection success rate. In performance evaluation of fabric inspection, not only does machine evaluation play an important role, experienced industrial practitioners also determine the degree of success in automated inspection. Although it is inherently subjective, only practitioners realize clearly what their customers request and demand in the final product (e.g. error rate in production) for delivery.

3. Methods of defect detection for p1 group

With reference to Fig. 5, there are six approaches under the non-motif-based category: statistical, spectral, model-based, learning, structural and hybrid approaches.

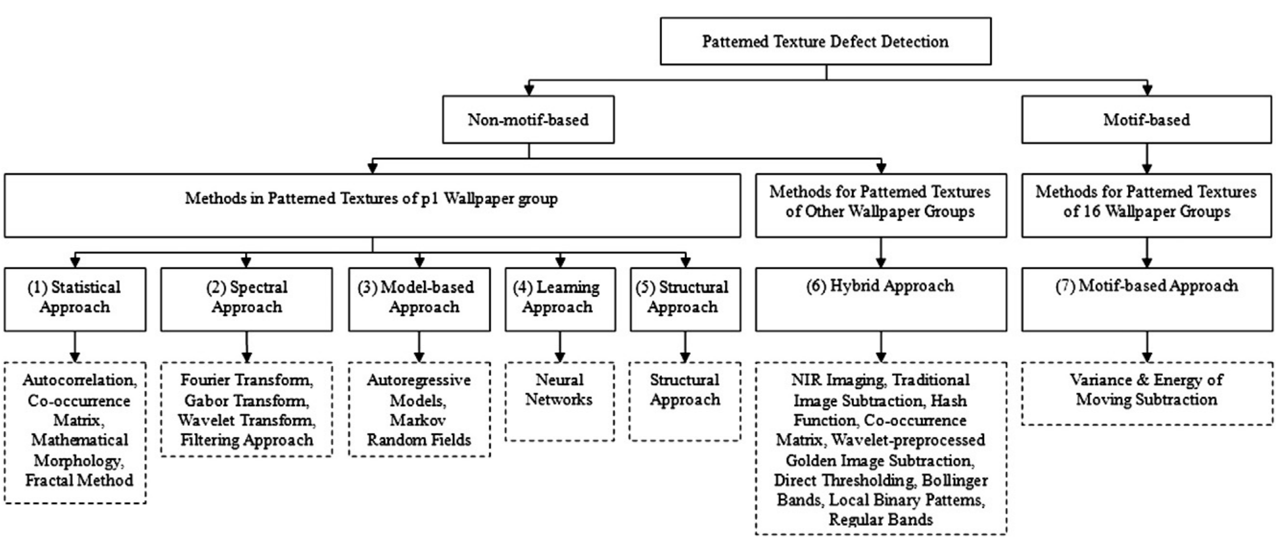

Fig. 5. Different approaches for patterned texture defect detection.

Table 1
Definitions of true positive, false positive, true negative, false negative in defect detection.

	Actually defective	Actually defect-free
Detected as defective	True positive (TP)	False positive (FP)
Detected as defect-free	False negative (FN)	True negative (TN)

3.1. Statistical approach

In statistical approach, spatial distribution of gray values is defined by various representations [51,52] such as auto-correlation function, co-occurrence matrices, and fractal dimension. Table 2 shows a summary of detection success rate of various methods in statistical approach.

3.1.1. Auto-correlation function

Auto-correlation function (AF) [22] measures spatial frequency and depicts maxima [15] at multiple locations corresponding to the length (or width) of repetitive primitive on an image.

The intensity of maxima stays constant for a repetitive primitive that is perfectly replicated throughout the fabric, or changed dramatically for imperfection in replication. It helps to determine the perfection of repetitive unit replication (Fig. 6) in plain and twill fabric image. For fabric defect detection, Wood [18] utilized a 2D AF to describe the translational and rotational symmetry of an image at plain carpet. However, no explicit result was given. Besides, AF calculates the period length of a pattern on the polar plot using a regularity approach [45], and the results are compared with the morphological approach (see Section 3.1.3). However, AF [22] can misinterpret a fine texture and cannot analyze a texture without a reference frame of tonal primitive.

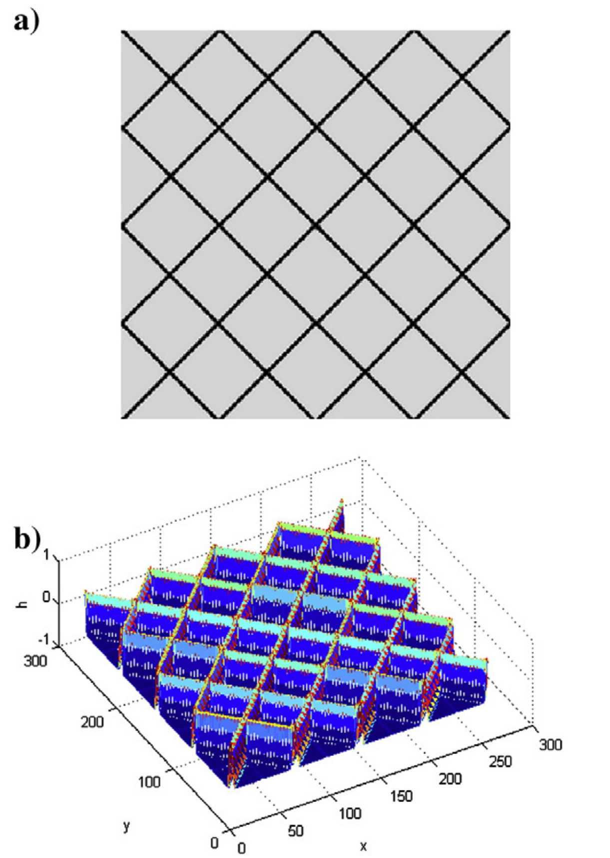

Fig. 6. (a) A pattern, and (b) a 3D plot of an auto-correlation result that shows peaks of periods for patterns in (a).

3.1.2. Co-occurrence matrix

Co-occurrence matrix (CM), originally proposed by Haralick et al. [53], characterizes texture features as second-order statistics by measuring 2D spatial dependence of the gray values in a CM for each fixed distance and/or angular spatial relationship. For twill fabric, Tsai et al. [14] applied CM to extract six image features as input parameters for a back-propagation neural network algorithm. A detection success rate of 96% was achieved with 25 images (5 defect-free and 20 defective images). Latif-Amet et al. [9,10] proposed the sub-band co-occurrence matrix (SBCM) method. They achieved a detection accuracy of 90.78% on 36 256×256 plain fabric images. The images from both examples above were acquired by a CCD camera with rather poor quality. Specifically, only four defective fabric samples of size 100×100 were shown in [14] and no explicit result after detection was given. Therefore, the reliability of these methods and how they applied to other fabric were both unclear. The CM is invariant under monotonic gray value transformations [22]. The spatial features of the CM are superior to that of AF because the co-occurrence probabilities can extract more information in one spatial distance, which is the measure between two pixel locations. Two main weaknesses of the CM [22] are poor performance in textures constructed by large-sized primitive and intensive computer requirements due to large number of adjacency pixels in calculation.

Table 2
Summary of detection success rates of previous methods in statistical approach in the p1 group.

Methods		References	Number of DFS for testing	Number of DS for testing	Detection success rate (%)
Statistical approach	Auto-correlation function	[18]	Unknown	Unknown	Unknown
	Co-occurrence matrix	[14]	5	20	96%
		[9,10]	17	19	90.78%
	Mathematical morphology	[15]	43	30	90.41%
		[57,58]	Unknown	Unknown	Unknown
		[45]	0	10 from Brodatz	60% for Brodatz
				120 from TILDA	54.13% for TILDA
		[59]	0	80 (from 5 classes of defects)	91.25%
		[60]	39	39	97.4%
		[61]	39	39	94.87%
			256	17	96.7%
	Fractal method	[65]	A total of 65 anonymous samples		93.85%
		[63]	16 images from Brodatz		Unknown
			36 synthetic textured images		
		[13]	40 (CCD scanner)	35 (CCD scanner)	96%
			40 (frame grabber)	40 (frame grabber)	
		[64]	14,378 (total of 7 datasets)	3222 (total of 7 datasets)	98.30% (best result from dataset 6)

Remark: DFS = defect-free samples, DS = defective samples.

3.1.3. Mathematical morphology

Mathematical morphology [54] extracts useful components in an image for the geometric representation and description of regional shape (e.g. boundaries and skeletons). It performs operations [55,56] such as erosion and dilation, for smoothing, sharpening and noise removal. The techniques used in the morphological approach (MA) are basically nonlinear. Six examples of the MA for fabric inspection are reviewed namely (a) [15], (b) [57], (c) [58], (d) [45], (e) [59] and (f) [60,61]. Briefly, the detection success rates of (a)–(f), except for (b) and (c), ranged from 54.13% [45] to 97.4% [60]. The most successful method is an optimal morphological filter designed by Mak et al. [60,61], for plain and twill fabric defect detection. The method reached accuracies of 97.4% [60] and 94.87% [61] (offline detection) over 78 images of 256×256 in size, of which there were 39 defect-free and 39 defective images from different defects, resolutions and textural backgrounds. There are 6 images out of 78 at [60] and 13 images out of 78 at [61], which are displayed in good quality. Mak et al. [61] further tested their approach on a real-time inspection machine for 276 frames of images sized 768×256 pixels (17 defective images and 259 defect-free images) and achieved 96.7% detection accuracy. Although it seemed reliable, no discussion was given for fabrics of other wallpaper groups. Kwak et al. [59] believed that the illumination and the distance between camera and fabric (leather) were two determining factors, in that the distance could be adequately adjusted by trial and error.

MA was compared with other methods in [15,45]. First, MA was compared with gray-level statistical approaches (auto-correlation function, mean and standard deviations of sub-blocks of images) in [15]. It achieved 90.41% detection rate while the statistical approach obtained 95.89%. Second, in [45], the regularity approach and the MA achieved detection accuracies of 100% and 60%, respectively. The regularity approach calculates two regularity features from the periodicity of the auto-correlation function in a polar co-ordinate form and outlier detection to detect defects. The merits and shortcomings of MA are as follows: (1) sensitive to defect size and shape; (2) better for segmentation due to the effect of clustering and noise removal; and (3) more localized than the regularity approach and is most appropriate on unidirectional texture, while its drawback is that it is not based on a single visual concept.

3.1.4. Fractal method

Fractals [52] are proficient and popular to model the statistical qualities like roughness and self-similarity on many natural surfaces [62]. Fractal methods are reported in [13,63–65]. The differential box-counting method [13] used differences in computing non-overlapping copies of a set of images and the method gave satisfactory results in all ranges of fractal dimension. Recently, Bu et al. [64] have compared with single fractal feature in [66] using four fractal features and support vector data description. In [64], it was tested with seven datasets of 14,378 defect-free and 3222 defective samples of plain and twill fabric of size 256×256. The detection rates ranged from 94.09% to 98.30%. Another leading method, proposed by Conci and Proenca [13], is a fractal image analysis system using a box-counting approach with an overall detection accuracy of 96%. Two sets of gray-level images were evaluated, of size 256×256, one set has 75 images and one set has 80 images. From their experience, a quality and consistent image acquisition, and lighting, are the two major challenges. In addition, the method in [65] achieved an accuracy of 93.85% for classifying 65 anonymous texture samples from the Brodatz texture database [67]. There are two further publications [68,69] referring this technique. Finally, in a comparison of this technique and another fractal method [68], the technique in [65] was found to be computational demanding even in noise-free texture samples.

3.2. Spectral approach

This section covers Fourier transform (FT), wavelet transform (WT), Gabor transform (GT) and filtering. Table 3 presents a summary of defection success rates of these methods.

Table 3
Summary of detection success rates of previous methods in spectral approach in the p1 group.

Methods		References	Number of DFS for testing	Number of DS for testing	Detection success rate (%)
Spectral approach	Fourier transform	[18,71], ([72,73]), ([74,75]), ([6,7])	Unknown	Unknown	Unknown
		[2]	0	Unknown	Unknown
		[66]	0	4	100%
	Wavelet transform	[40,41]	Unknown	Unknown	Unknown
		[80]	0	25	98%
		[39]	50	350	85% (images with noise)
					94% (images without noise)
		[19]	0	2	100%
		([48,81])	0	>3700	89%
		[38]	480	480	97.5% (known defect types)
			780	180	93.3% (unknown defect types)
		[77]	0	8	100%
		[78]	434	466	95.8%
	Gabor transform	[49,85]	Unknown	Unknown	Unknown
		[84]	0	8	100%
		[83]	0	35	82.86%
		[87]	25	25	Unknown
		[88]	0	3	100%
		[86]	0	20	95%
		[37]	Unknown	Unknown	Unknown (supervised approach)
			0	8	100% (unsupervised approach)
			0	13	100% (imaginary Gabor function)
		[91]	0	4	100%
		[82]	39	32	96.2% (plain, twill, denim fabrics)
			259	17	97.1% (twill fabric)
		[92]	0	4	75%
		[90]	Total of 32 images		Unknown
		[93]	360	360	Unknown (defect detection)
					87% (defect classification)
	Filtering approach	[95]	Unknown	Unknown	TP = 98.3%, TN = 90.6%
		([96,97])	0	1	100%
		[98]	0	12	100%

Remark: DFS = defect-free samples, DS = defective samples, TP = true positive, TN = true negative, brackets of references for the same group of researchers.

3.2.1. Fourier transform

FT is derived from the Fourier series [70]. The spatial domain is usually noise sensitive and arduous to locate defects while FT utilizes the frequency domain to characterize the defects. Wood [18] applied Fourier power spectrum to measure the coarseness of texture on plain carpet defect detection. Similarly, optical Fourier transform (OFT) methods were applied by Hoffer et al. [71] for plain cotton fabric, and by Casterllini et al. [72] and Ciamberlini et al. [73] for cotton and wool woven fabrics, Campbell et al. [74,75] for woven denim (twill) fabric. Hoffer et al. [71] presented an OFT to detect and identify the defects on an on-loom neural network based inspection machine. Casterllini et al. [72] and Ciamberlini et al. [73] recommended that OFT be installed in an on-loom machine to detect and identify defects. A regular periodic pattern would reveal a double series of peaks with horizontal and vertical locations by OFT, depending on the spatial frequencies of 2D grating corresponding to the weft and warp textures. By different techniques, the irregularities (defects) of grating generate a variation as a rise of the light intensity between adjacent peaks. These approaches are vulnerable to the on-loom machine vibration and electrical interference from surrounding machinery, but insensitive to small defects. At this early stage, the research of [18,71–75] was only tested on limited fabric samples.

Chan and Pang [2] applied a central spatial frequency spectrum for defect classification of plain fabric and only a few defective samples from four classes of plain fabric defects were evaluated. Fourier bases usually lack local support (i.e. information) in the spatial domain, and two similar global FT image reconstruction schemes, [6,7], were proposed for improvement. An inverse FT can remove the line patterns (reported in [6]) as well as periodic and repetitive patterns of any statistical texture (focused by [7]). Various textures were tested in [6] (7 sets) and [7] (8 sets). The only explicit detection result, given by Chiu et al. [66], was Fourier-domain maximum likelihood estimator (FDMLE) which was based on a fractional Brownian motion model for detecting fabric surface defects. Four defective images of size 128×128 were shown to be successfully detected by FDMLE. The method was invariant to geometric transformation such as rotation, position shift, gray-level shift and size rescaling of an image. Though all the methods in [2,6,7,66] were claimed to be successful in defect detection, their reliability was unknown.

3.2.2. Wavelet transform

Wavelet representation [76] is a theory for multi-resolution signal decomposition. As the basis functions of FT are sinusoids, wavelet transforms (WT) [55] are based on small waves of varying frequency and limited duration called wavelets. WT offers localized information (more local support than FT) from horizontal, vertical and diagonal directions on any input image. For plain and twill fabrics defect detection, WT [19,38,40,41,48,77–81] is commonly used for the feature extraction. Other previous WT approaches include Fuzzy Wavelet Analysis [80], multiscale wavelet method [19], WT image restoration schemes [40,41] and adaptive level-selecting scheme to analyze the CMs from approximated sub-images [77]. Detection success rates of these methods ranged from 98% to 100%, except for [40,41]. The main problem of the methods [19,40,41,77,80] was that their reliability was not known due to limited number of samples test.

More outstanding evaluation results of WT were from (a) [39], (b) [48,81], and (c) [38,78] with detection success rates between 85% and 97.5%. The Karayiannis group [39] proposed a back-propagation NN with 16-tap Daubechies wavelet decomposition on a real-time machine and achieved defect classification accuracy of 85% (with noise in input images) and 94% (without noise) for 350 defective and 50 defect-free images. Meanwhile, the added noise level was not specified. An on-loom fabric inspection system by Sari-Sarraf and Goddard [48,81] proposed to use WT and edge fusion as preprocessing tools to attenuate the background texture and accentuate the defects on sheeting, filament-yarn and spun-yarn fabrics. It reached an 89% detection success rate over 3700 images of fabrics, containing 26 different kinds of defects. The fabric images were captured by high solution vibration-free 4096-element line-scan camera while the defects occur during weaving. Though the accuracy rate was not high enough, their method was more reliable than those methods in [19,77,80] based on this quantity of test samples.

In general, wavelet basis is heuristically selected to capture the most outstanding features of defects. Yang et al. [38] designed a state-of-the-art technique of an adaptive wavelet-based feature extractor with a Euclidean distance-based detector for plain and twill fabrics (Fig. 7). It achieved a detection rate of 97.5% with known defects (480 defect-free and 480 defective samples), and dropped to 93.3% with unknown defects (780 defect-free and 180 defective samples). The samples were of size 32×32 and all images were of good quality. The only question left was whether the technique can be applied to other wallpaper groups. Yang et al. [78] later compared a new discriminative feature extraction (DFE) method with five other WT-based classification methods on 9 classes of samples (8 defect and 1 defect-free classes) of plain and twill fabrics. The DFE method outperformed the rest; however fabric defect classification accuracy slightly decreased to 95.8% for a larger database of plain fabric samples (434 defect-free and 466 defect samples) when compared to that of [38].

3.2.3. Gabor transform

The general form of Gabor function [37] is in a complete non-orthogonal basis set and its impulse response is in the 2D plane. As it is hard for a wavelet base to describe a texture pattern from the wavelet coefficients, Gabor filter (GF) attempts the optimal joint localization in spatial and spatial-frequency domains [37]. There exist two categories of implementations of Gabor filters [82,83]: (1) Filter bank consists of a huge set of filters with predetermined parameters in frequency and orientation to effectively cover the frequency plane. However, it is computationally intensive and dramatically affects recognition quality. (2) Implementations of optimal filters [83] that use fewer filters, but a correct choice is hard and crucial.

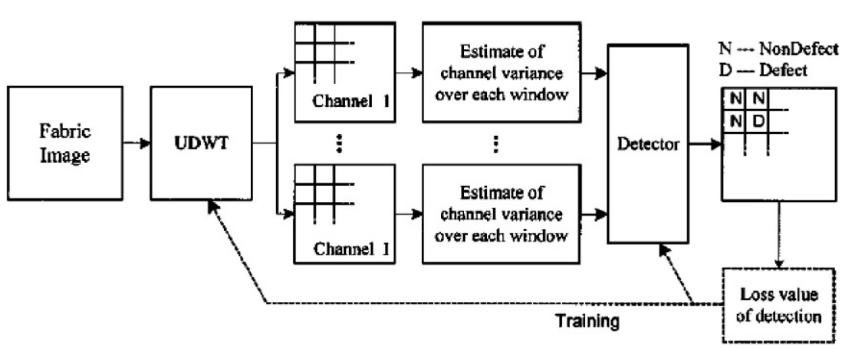

Fig. 7. A wavelet-based method [38] with a feature extractor with a Euclidean distance-based detector (courtesy of Dr. X.Z. Yang [38]).

A decade ago, Escofet et al. [84] applied multi-scale and multi-resolution GF on fabric inspection. Besides work reported in [6,7,40,41], they suggested a single 2D GF approach in [49] and a 1D GF approach in [85]. For the latter, computational complexity is significantly decreased from 2D to 1D in Gabor space. At the same time, Ding et al. [86] proposed a similar two 1D Gabor filter and achieved a detection accuracy of 95% for 20 images from a plain fabric database. Yet their threshold value could only detect a certain type of defect. Similar to [49], Bodnarova et al. proposed optimal 2D GF in [83,87], in which 82.86% detection accuracy was achieved in [83]. Recently, an on-loom inspection [88] has been proposed for homogenous fabric based on the energy response from the convolution of GF banks in frequency and orientation domains. In short, the main weaknesses of those techniques described in [49,83–88] were limited testing samples and their reliability on a larger dataset is still an open question.

Gabor transform (GT) is a special case of short-term Fourier transform. GT can be integrated with other approaches like wavelet transform. Kumar and Pang [37] utilized Gabor wavelet features on plain and twill fabrics in three schemes. No explicit result was provided in the 1st scheme (supervised approach) and 100% accuracies were claimed in both the 2nd (unsupervised approach, resembled the one in [89]) and 3rd (web inspection) schemes. Liu et al. [90] proposed an optimized GT method (based on the 2nd scheme) and claimed to have superiority to the 2nd scheme, but no explicit comparison was provided. More recently, Liu and Han [91] proposed an optimal individual filter, from a set of Gabor wavelet filters, with a similar 1st scheme to that in [37]. Ogata et al. [92] suggested a new image visualization technique by an interface of plasma display panel to display an electromagnetic wave shield mesh for twill fabric defect detection. It applied 2D Discrete Fourier transform to detect the global defects and an optimal GF to segment the local defects. Reliability of these methods [37,91,92] is not sure due to few samples. Recently, Li et al. [93] integrated GT with a Gaussian mixture model for plain fabric defect detection, but the results were not conclusive (only 9 detected images shown) with a classification success rate of 87% from 360 defective images of 9 classes of defects.

Among the GT methods, Mak and Peng [82] achieved the best detection result on a fair amount of testing samples. They applied a Gabor wavelet network to extract optimal texture features from a defect-free image, then a well-tuned real-valued GF was employed for detecting defects. The detection success rates [82] were 96.2% (39 defect-free and 32 defective images sized 256×256 from plain, twill and denim weaving fabrics acquired by a flat-bed scanner) and 97.1% (259 defect-free and 17 defective images sized 768×256 from twill fabric captured by a line-scan camera with front and back lighting). It revealed that both acquisition sources did not make a big difference in the detection accuracy. Yet, the reliability of their method when applied to other wallpaper groups of fabrics was not explored.

3.2.4. Filtering approach

Filtering [52] is utilized in many applications (e.g. image enhancement) and performed [55] between an image neighborhood and a filter mask. Two kinds of filtering methods [55] are: (1) frequency domain filtering based on Fourier transform, and (2) spatial filtering based on direct operations on image pixels. Both are sensitive to noise [94] in the image. Neubauer [95] recommended a defect segmentation method based on multiple linear filters (including three separable convolution filters as 1st-order statistics). Depicting only one fabric sample in poor quality, the true positive rate and the true negative rate of detection were 98.3% and 90.6%, respectively. An 8-parameter 2D lattice filter [96,97] was utilized to detect defects on raw fabrics. To reduce the computation complexity for detection, a Multi-Scale Differentiation Filtering (MSDF) method [98] was suggested with the help of B-spline. The defects from small to large size of 12 plain fabric image sized 256×256 (acquired by camera on real-time air-jet looms) were outlined after detection. The MSDF method was successful in suppressing the background texture, and seemed effective to detect different defects, and had a high sensitivity. Yet, it produced distorted output for large-scale defects. No explicit results were presented in [95–98] and their reliability on a large database was not clear.

3.3. Model-based approach

A random field [99] of an image is a stochastic modeling (SM) by a simple function of an array of random variables. In general, SM in image processing can be broadly classified into three classes: covariance, 1D and 2D models. Autoregressive (AR) model belongs to the 1D class. The 2D models include casual, semi-casual and non-casual predictions. Markov random field (MRF) is one of the non-casual predictions. For the sake of the convenience in comparison with other approaches, Table 4 offers a summary of recent methods.

3.3.1. Autoregressive model

AR model [22] exploits the linear dependence between different pixels of a textural image. It can capture any textural feature and characterize the texture. Serafim [100,101] proposed a 2D AR model for feature representation and cooperation with multi-resolution pyramids of natural surface classification and leather defect segmentation. Basu and Lin [102] studied the use of a multi-scale AR model on tress as a texture model for floral-pattern (the p2 group), checkered-pattern (the p4 group) and carpet-pattern (the p1 group) fabric samples. The result was promising as the model is computational fast and efficient. A 1D AR method was used [103] for web inspection using a CCD camera as real-time defect detection, with only successful testing on a defective plain fabric and some synthesized textural images. Lighting as pointed out in [100,103] was crucial in the setup of the AR method. The problem of [100–104] was similar to many previous approaches that no result was given. The AR model approach, in [100,101], was sensitive to very small width defects and easily affected by the lighting due to similarity between the defects and leather background. On the other hand, it was insensitive to the translation of pattern on texture in [103].

3.3.2. Markov random fields

MRF [105] can be applied in many image processing areas: texture segmentation [106,107] and classification [108,109]. It can combine both statistical and structural information [110] in pattern recognition. Its principle stresses that pixel intensity in an image depends on the neighboring pixels only. Cohen et al. [111] utilized Gaussian MRF (GMRF) to model defect-free texture on fabric images and that the GMRF model [108] was a stationary non-causal 2D AR process. Derived from the model, defect detection was cast as a statistical hypothesis testing problem. Six 256×256 images with various defects were tested in three setups. Although their method was successful in detecting all defects on six images with no false alarm, no evaluation on either defect-free images or a larger size of database was offered. Ozdemir and Ercil [112] suggested applying a MRF model in fabric

Table 4
Summary of detection success rates of previous methods in model-based approach in the p1 group.

Methods		References	Number of DFS for testing	Number of DS for testing	Detection success rate (%)
Model-based approach	Autoregressive models	([100,101]), [102–104]	Unknown	Unknown	Unknown
	Markov random fields	[112,113]	Unknown	Unknown	Unknown
		[111]	0	6	100%

Remark: DFS = defect-free samples, DS = defective samples, brackets of references for the same group of researchers.

Table 5
Summary of detection success rates of previous methods in learning approach in the p1 group.

Methods		References	Number of DFS for testing	Number of DS for testing	Detection success rate (%)
Learning approach	Neural networks	[116]	A total of 128 images		86.2%
		[117]	Unknown	Unknown	Unknown
		[118]	0	160	91.88%
		[119]	0	240	94.38%
		[120]	0	32	91% (hole), 100% (oil stain)
		[121]	Unknown	Unknown	99%
		[122]	0	270	83.4%

Remark: DFS = defect-free samples, DS = defective samples.

Table 6
Summary of detection success rates of previous methods in structural approach in the p1 group.

Methods		References	Number of DFS for testing	Number of DS for testing	Detection success rate (%)
Structural approach	Structural approach	([46,47])	Unknown	Unknown	Unknown
		[11]	0	5	100%
		[123]	0	1	100%
		[124]	0	12	95% (correlation approach) 80% (blob detection approach)

Remark: DFS = defect-free samples, DS = defective samples, brackets of references for the same group of researchers.

inspection as well as comparing the detection result between a MRF based method and a Karhunen–Loeve (KL) based method. Without clear illustration of detection result on the four defective images sized 256×256 (fair quality in [112]), the MRF approach (0.33 s) outperformed the KL approach (3.13 s) in execution times. Though MRF models captured local spatial contextual information [52,112] in an image, feature extraction was weak at identifying small defects on fabric according to [94]. A recent method [113] has proposed a wavelet-domain Hidden Markov Tree model with a level set segmentation technique, but no detailed evaluation was given.

3.4. Learning approach

3.4.1. Neural networks

Neural network (NN) models [51,114] employ organization principles (e.g., learning, or generalization) and can perform many tasks [115] such as feature extraction, segmentation and optimization. Its limitations [115] include its black-box character, difficulty in coping with abundance of features and concomitant variations in scale, position and orientation. Apart from those methods partially using NN in [14,19,39,48,71,74,82,95], NN-oriented fabric inspection methods are depicted in Table 5. Stojanovic et al. [116] suggested a three-layer back-propagation artificial neural network for low cost fabric defect detection with off-the-shelf components. It achieved a detection accuracy of 86.2%. Similarly, a cost-effective feed-forward NN architecture based on principal component analysis (PCA) was proposed in [117]. A three-layer back-propagation (BP) NN was proposed by Kuo et al. [118] for plain white fabric defect detection (Fig. 8). From four defect classes, 160 defective images (acquired by 1×4096 high resolution line-scan camera) were tested with a defect recognition accuracy of 91.88%. Its merit was to model a high dimensional system by non-linear regression algorithm. For the same kind of fabric, another BP network [119] was presented with a pre-processed filtering step. It was tested on 240 defective images (by an area-scan camera) from four classes and offers 94.38% accuracy. A recent BP NN [120] has accomplished 91% and 100% detection success rates for hole (16 images) and oil stain (16 images) of twill fabric, respectively. Though the detection accuracies in [118–120] were high, the image sampling quality was poor and the reliability was unknown. A NN method [121] achieved over 99.9% accuracy in both off-line (2 plain weave fabric samples of unknown sizes) and on-line (a fabric sample of unknown size) defect detections. However, without accurate sample size, the result in [121] was not suitable for comparison. Lastly, a recent radial basis function method [122], using the same feature extraction mask as in [117], achieved 83.4% defect classification for 270 images, although it is not promising compared to other NN methods.

3.5. Structural approach

Structural approach (SA) [52] usually considers the texture as a composition of texture primitives. By certain placement rules, texture is replicated by a primitive. Structural texture analysis mainly composes of two steps: extraction of texture elements and inference of the placement rule. The usual criticism [52] of SA is that it only performs well on very regular texture, such as the four recent methods as shown in Table 6. Chen and Jain [11] proposed a SA in a study of skeleton and background texture to identify defects from knitted fabric images. Without much illustrations and clear measurement of performance, five 128×128 images from various defective fabrics were evaluated. Bennamoun and Bodnarova [123] presented a SA called texture blobs detection. Texture blobs possess many properties, such as size, elongation and orientation, which can uniquely characterize the underlying texture. One of its disadvantages was being computational intensive. Maximum Frequency Difference (MFD) comparison [124] (improved solution of [123]) was applied against a matching window in a defect-free sample. It compared the modified blob detection algorithm with normalized cross-correlation algorithm on twelve defective plain and twill fabrics images. Surprisingly, the correlation approach obtained a higher detection success rate of 95% while the blob detection approach achieved 80%. For this reason, only a small statistical change in the background can lead to a significant change in the MFD which leads to high false alarm. In addition, structural defects (same as irregularities) and pattern regularity features were defined for outlier detection in [46,47]. Two drawbacks of structural defects are: (1) impossible to tune the algorithm to a particular geometry of a defect, (2) not applicable to neither structures of low regularity, nor defects size smaller than a window with 2 period length of the pattern structure. In short, the image quality was poor in [11,123,124] with no explicit result in [46,47]. Also, the reliability of their methods is doubtful.

3.6. Other methods for p1 group

There exist other methods for fabric defect detection for p1 group (Table 7). For instance, the most recent method [125] dealt with one

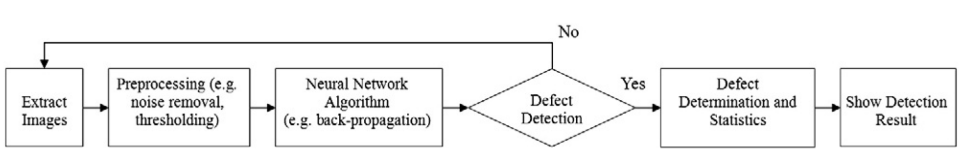

Fig. 8. Procedure of a back-propagation NN proposed by Kuo et al. [119].

Table 7
Summary of detection success rates of other methods in the p1 group.

Approaches	Methods	References	Number of DFS for testing	Number of DS for testing	Detection success rate (%)
Statistical	Histogram equalization	[125]	Unknown	Unknown	Unknown
Spectral	Radon transform	[126]	Unknown	Unknown	Unknown
Spectral	Principal component analysis	[127]	50	150	98%
Modeling	Gaussian mixture model	[128]	Total of 360 images		TP = 93%, TN = 95%

Remark: DFS = defect-free samples, DS = defective samples, TP = true positive, TN = true negative.

specified defect: pills, in cotton fabric surface; and utilized thresholding on histogram equalized images. A spectral approach using Radon transform was applied in [126] for unknown fabric. A PCA method [127] that utilized fuzzy C-mean clustering based on particle swarm optimization offered 98% recognition rates for 250 testing images from 4 classes of plain fabric samples (defect-free, weft-lacking, warp-lacking and oil stain). However, this result was doubtful because limited samples are given in poor quality and no clustering result is shown. Gururajan et al. [128] proposed a Gaussian mixture model with Expectation-Maximization to detect one specific kind of defect, soil (stain) release, for 360 stain images from four types of fabrics. A true positive rate of 93% and a true negative rate of 95% were achieved for 6 types of soils under four categories of laundering treatments. Regarding repeatability and reproducibility of the scheme, it was also verified under various scanners and different light intensities.

4. Methods for other wallpaper groups (hybrid approach)

There are not many published methods for the other sixteen wallpaper groups compared with that of the p1 group. The most common patterned textures for investigation were lace [16,17,42,43] and Jacquard fabrics [20,44,129–134]. The methods used could be broadly classified as template-matching approach, and statistical & spectral approach, which are termed hybrid approach. On the other hand, a minority approach such as near-infrared (NIR) method in [50] was a hardware approach to utilize NIR illumination instead of the traditional visible light source. In [50], there were two light sources, NIR and white visible light, for image capturing. A NIR image was acquired when the visible light is off and the NIR light-emitting diodes (LEDs) are on. A camera could capture the reflected diffuse NIR light from the fabric. The defects were usually undistinguishable in the usual visible light image. Table 8 depicts a summary of the detection success rates of various methods with respect to different wallpaper groups.

4.1. Template-matching approach

A common template-matching approach is the Traditional Image Subtraction (TIS) method (same as an exclusive-OR (XOR) operation for printed circuit boards inspection [21]). TIS subtracts a test image from a perfect master image and works perfectly if the input image is precisely-aligned. Sandy et al. [16] first proposed the TIS method for defect detection on lace, whose image was usually noisy and distorted with difficulty in alignment. Later on, Tao et al. [43] proposed a similar subtraction approach, whereas Yazdi and King [42] and Farooq et al. [17] proposed a mechatronic approach for perfect alignment. TIS was very sensitive to noise and was found to be unsuccessful in a preliminary test of [44].

4.2. Statistical & spectral approach

Many methods fall under this category. A gray relational analysis [132] on co-occurrence matrix features was used to investigate correlations of the analyzed factors among the selected features in a randomized factor sequence for Jacquard fabric inspection. The detection accuracy was 94% for 50 defective images of size 256 × 256 from the p2 group. Yet, only four defective samples were displayed and no detection result was shown so that its reliability and generality were not known. Hash function method, utilizing the offset properties between defect-free and template patterned textures, was a 1D approach and sensitive to small changes in pattern. Four types of Hash function detected defects from simple to complex textures in [130,135]. Previously, an image block densitometrical profile [136], equivalent to the checksum Hash function in [130,135], was proposed. No precise detection result in [130,135,136] was given. Test of the Hash function method evaluated in [44] was poor.

The wavelet-preprocessed golden image subtraction (WGIS) method (improved version of GIS in [137]) was a mixture of statistical and spectral approaches for the Jacquard fabric defect detection [44,133]. The basic GIS and WGIS methods had detection accuracies of 78.33% and 96.7%, respectively, for 60 images (the pmm group) sized 256 × 256 in good quality. The WGIS method outlined the defective regions after detection, but it was weak to detect defects at some extreme simulated patterns like charter-box pattern. The Direct Thresholding (DT) (spectral approach) [44,133] obtained good Haar wavelet sub-images in the horizontal and vertical directions for detection and achieved 88.3% detection accuracy, using the same database of the WGIS method.

The Bollinger Bands (BB) method, originally for financial technical analysis [138], was based on moving average and standard deviation. It

Table 8
Summary of detection success rates of previous methods in each approach in other 16 wallpaper groups.

Methods	References	Groups of textures in reference	Number of DFS for testing	Number of DS for testing	Detection success rate (%)
NIR imaging (hardware)	[50]	Unknown	Unknown	Unknown	Unknown
Traditional image subtraction[a]	[16,17,42,43]	Unknown	Unknown	Unknown	Unknown
	[44]	pmm	1	1	0%
Hash function[b]	([130,135]), [136]	Unknown	Unknown	Unknown	Unknown
	[44]	pmm	30	30	Unknown
Co-occurrence matrix[b]	[132]	p2	0	50	94%
GIS[b]	[44]	pmm	30	30	78.33%
WGIS[b]	([44,133])	pmm	30	30	96.7%
Direct thresholding[b]	([44,133])	pmm	30	30	88.3%
Bollinger bands[b]	([129,133])	p2, pmm, p4m	167	171	98.59%
Local binary patterns[b]	[134]	p2, pmm, p4m	Unknown	Unknown	p2: 97.4%, pmm: 96.5%, p4m: 97.6%
Regular bands[b]	[20]	p2, pmm, p4m	80	86	99.4%

Remark: DFS = defect-free samples, DS = defective samples, GIS = golden image subtraction, WGIS = wavelet-preprocessed golden image subtraction.
[a] For template-matching approach.
[b] For statistical approach, brackets of references for the same group of researchers.

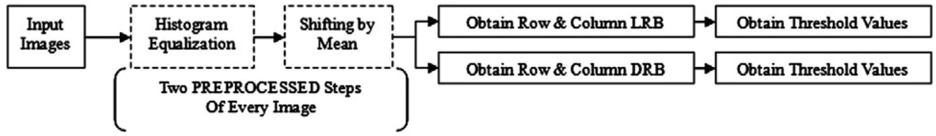

Fig. 9. Training stage of the Regular Bands method (LRB = light regular band, DRB = dark regular band).

was extended from a 1D approach into a 2D approach for Jacquard fabric inspection [129,133]. The detection accuracy achieved 98.59% for 336 fabric images in good quality from three groups (pmm, p2, and p4m). The BB method was shift-invariant across patterned texture and its mathematical definition was simple. In addition, it was able to outline defective regions after detection. Compared with WGIS, DT and Hash function, it was computational fast. However, one of its weaknesses [129,133] was on detecting defects with slight color difference from texture pattern. Local binary pattern (LBP) feature [134], originally used in texture classification, was proposed for fabric image. This feature was rotational invariant and multi-scale. Defect detection was done by comparing between reference and test feature vectors. Evaluation was performed on twill and plain fabrics (p1 group) and Jacquard fabrics (the same database of p2, pmm and p4m groups in [129]). Without specified quantity of samples, the detection success rates for the p1, p2, pmm and p4m groups were 97.1%, 97.4%, 96.5% and 97.6%, respectively. It outperformed the BB method for p2 and p4m groups, and the WGIS method for pmm group. It was much more computational efficient when compared to the WGIS and BB methods.

The Regular Bands (RB) method [20] has been developed as a regularity analysis (RA) for patterned texture inspection. A break in periodicity is considered to be a defect. In short, the WGIS, DT, BB and RB methods can be regarded as RA. Similar to the BB, the design of RB was based on moving average and standard deviation, but with some modifications in pre-processing (Fig. 9) and its theoretical design. The testing database had 166 images samples sized 256×256 from three types of fabrics (same as the BB method) in good quality. Its 99.4% detection accuracy outperformed the WGIS, DT and BB methods. RB inherited most strengths and weaknesses of BB. Moreover, it was superior to BB owing to more sensitivity to small defects, easier implementation and only requiring knowledge of the period length of a repetitive pattern.

5. Motif-based methods for 16 groups

As mentioned in Section 1, a generalized motif-based defect detection method [3,8] for 16 out of 17 wallpaper groups has recently been developed. As the p1 group has only one motif, it does not suit the 1-norm metric design which requires at least two different motifs. Therefore, it is excluded from the discussion here. It was also based on a statistical approach, with a mathematical design on variance and energy of 1-norm metric, between any two motifs in lattices of patterned texture. In particular, the energy-variance space was proposed and a Max–Min decision region (MMDR) is formulated (Fig. 10). It achieved a promising detection success rate of 93.86% (Table 9). No other published methods were able to handle such a large number of wallpaper groups of 2D patterned textures, and hence this result was more general and relatively reliable than all other published approaches. The MMDR of the motif-based method was further extended by an ellipsoidal decision region (EDR) [139] in order to deal with ambiguous false-positive and false-negative cases. With the same conditions as the MMDR, the fabric samples of the p2, pmm and p4m were evaluated. The detection success rate of the p2 group was enhanced from 93.43% to 100% and the pmm group from 95.90% to 96.72%, while the p4m group resulted in the same detection success rate. It showed that the EDR was superior to the MMDR in that sense. It also showed the possibility of optimization and yielded a route for further extension of the motif-based method. Lastly, it was believed that the motif-based approach could be further extended to the p1 group, thus covering all 17 groups.

6. Summary

Defect detection can be affected by factors such as illumination and quality of acquired images. In general, a perfect detection success rate is almost impossible to achieve as the quantity and type of patterned images for evaluation increase. It is observed that if the developed method is only for a specific wallpaper group, the defect detection success rate can be quite high. However, if the method is generic and applicable to many wallpaper groups (like the motif-based approach), the overall defect detection success rate would be lower. This paper has reviewed the current-state-of-the-art defect detection methods of both non-motif-based and motif-based approaches. In summary, Tables 10, 11, 12, 13 and 14 describe the strengths and weaknesses of

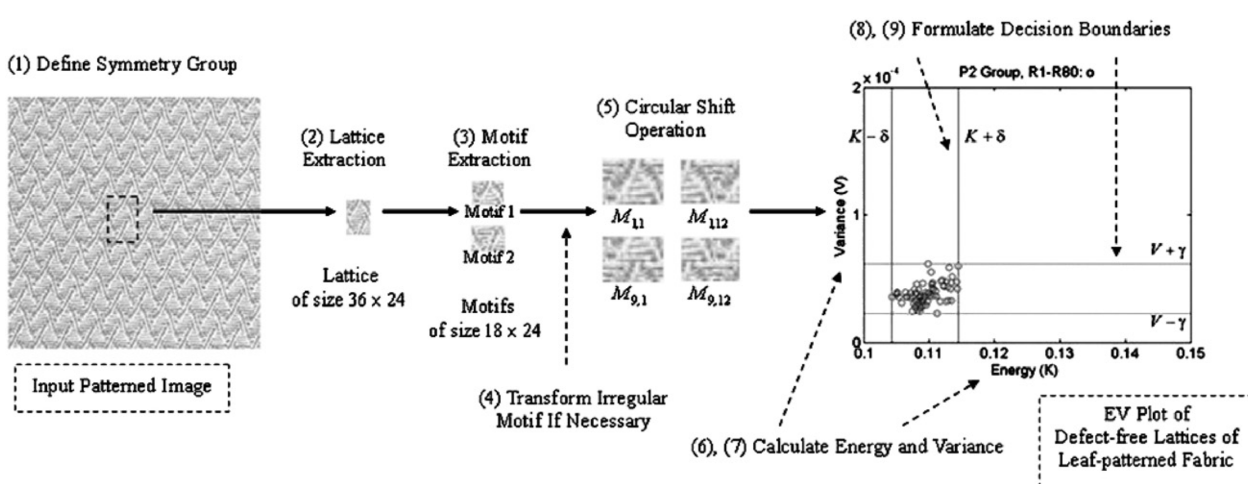

Fig. 10. Block diagram of formulation of decision boundaries with 9 steps: (1) define symmetry group, (2) lattice extraction, (3) motif extraction, (4) transform irregular motif, (5) circular shift operation, (6) and (7) calculate energy and variance, and (8) and (9) formulate decision boundaries (courtesy of [3]).

Table 9
Summary of detection success rate of motif-based method of 16 wallpaper groups.

Method	References	Groups of textures	Number of DFS for testing	Number of DS for testing	Detection success rate (%)
Motif-based	([3,8])	All 16 groups except p1 group	340	233	93.86%

Remark: DFS = defect-free samples, DS = defective samples, brackets of references for the same group of researchers.

different methods for all the 17 wallpaper groups. In Table 10, statistical methods enable us to characterize spatial relationship of pixels and provide much useful information such as regularity, coarseness, self-similarity and uniformity. Their weaknesses are their inability to analyze a texture without a reference and to work with large textural primitives. In Table 11, spectral methods utilize a new domain after different transforms to analyze the patterned texture. They offer multi-resolution images to reduce the computational costs on down-sized images. However, methods like WT and GT are still computational demanding and filtering is sensitive to noise. In Table 12, model-based methods are able to characterize the linear dependence between different pixels of a patterned texture image and capture the local contextual information. Yet, they are sensitive to illumination setup and poor in identifying small defects on fabric. NN's learning approach has generalization ability, but cannot cope with abundant features, concomitant variations, and small defects. Lastly, SA can characterize texture as a composition of textural primitive, but it only performs well on very regular texture. In Table 13, some recent non-motif-based methods have been developed for 16 wallpaper groups. BB and RB methods are outstanding in both of success rates and design simplicity. The only criticism for them is an inefficiency of defect detection near the borders of patterned texture. The motif-based method in Table 14 is promising and offers a new direction to other researchers that a balance between the generality and detection success rate can be achieved.

7. Future direction and conclusions

This section provides insights, synergy of different approaches and suggestions for future research in automated fabric defect detection.

7.1. Insights

7.1.1. Limited fabric types for defect detection

Although conventional detection methods deal with fabric based on its pattern or texture which would appear as complex variations and combinations of primitive pattern consisting of dot, line, strips, flowers, etc., all kinds of fabrics can be classified into only 17 wallpaper groups [3,8]. This greatly reduces the difficulty on the development and verification of methods for automated fabric detection. Essentially, no matter how complex a fabric pattern or texture would appear, it must belong to one of the seventeen pattern groups. Methods and results developed for a fabric pattern group should share common features and properties. This classification would help to handle the vast variety of fabrics available in the textile industry and market.

7.1.2. Generality issue

Most published methods for patterned fabric detection can only work on some wallpaper groups of patterns such as the p1 group, but fail on the other wallpaper groups. There is a huge demand to develop a defect detection method that is applicable to many if not all wallpaper groups. The method should also be extensively evaluated on a large database of samples.

Table 10
Strengths & weaknesses of defect detection of statistical approach for p1 wallpaper groups of non-motif-based approach.

Methods		Strengths	Weaknesses
Statistical approach	Auto-correlation function	1. Measure regularity, fitness, coarseness of texture 2. Determine the dimension of a repetitive unit	1. Can misinterpret a fine texture 2. Cannot analyze a texture without a reference frame of tonal primitive
	Co-occurrence matrix	1. Characterize spatial relationship of pixels 2. Invariant under gray value transformation	1. Intensive computation 2. Unable to capture shape aspects of tonal primitive 3. Not working well for texture with large-size primitive 4. May miss some valuable information in the undirected distance
	Mathematical morphology	1. Extract geometric representation and description of region shapes 2. Perform as spatial filter for noise removal, edge detection or feature extraction 3. Sensitive to defect size and shape	Without a single visual support
	Fractal	Characterize roughness, self-similarity on natural textures	Computational demanding

Table 11
Strengths & weaknesses of defect detection of spectral approach for p1 wallpaper groups of non-motif-based approach.

Methods		Strengths	Weaknesses
Spectral approach	Fourier transform	1. Utilize the frequency domain to characterize the defects 2. Apply power spectrum to measure coarseness of texture 3. Central spatial frequency spectrum is invariant to rotation, translation, rescaling	1. Lack support in spatial domain 2. Unable to detect random patterned texture
	Wavelet transform	1. Provide multi-resolution of image 2. Enable to perform as smoothing filter 3. Enable to capture the most outstanding features of all defects 4. Wavelet filter can be tailor-made	Adaptive wavelet transform is computational demanding
	Gabor transform	1. Offer a joint spatial and spatial-frequency representation 2. Give optimal joint localization in both spatial and spatial-frequency domain 3. Filter bank provides a high dimensional feature space 4. Optimal filter or 1D Gabor filter with ring-projection can reduce computational effort	1. Filter bank is computational intensive 2. 2D Gabor filtering is computational expensive
	Filtering approach	Enable to perform enhancements on image quality, noise reduction and feature of interest	Sensitive to noise

Table 12
Strengths & weaknesses of defect detection of model-based, learning and structural approaches.

Methods		Strengths	Weaknesses
Model-based approach	Autoregressive models	1. Characterize the linear dependence between different pixels of a texture image 2. Characterize micro-textures of textures 3. Sensitive to very small width defects 4. Computational fast and efficient	1. Easily affected by the lighting setup 2. Insensitive to the translation of pattern on texture
	Markov random fields	1. Capture the local (spatial) contextual information 2. Combine both statistical information in pattern recognition	Weak at identifying small defect on fabric
Learning approach	Neural networks	1. Enable to learn and generalize the data to give reasonable output 2. Has properties of adaptivity, fault tolerance and distributed representation	1. Black-box character 2. Difficulty of coping with abundance of features and concomitant variations 3. Unable to detect small defects
Structural approach	Structural approach	1. Characterize texture as a composition of texture primitives	1. Only perform on very regular texture 2. Computational intensive

Table 13
Strengths & weaknesses of defect detection for 16 wallpaper groups of non-motif-based approach.

Methods	Strengths	Weaknesses
NIR imaging (hardware)	Contrast reduction of the superstructure signal (bands, squares) in the NIR image facilitates fabric inspection and defect segmentation in basic structure	High energy signal usually constitutes noises leading to misdetection
Traditional image subtraction	1. Perfect for ideal images 2. Fast computation	1. Sensitive to noise 2. Difficult for precise alignment
Hash function	Time-saving due to 1D approach	1. Sensitive to noise 2. Inability to outline defective regions
Co-occurrence matrix	1. Characterizes spatial relationship of pixels 2. Invariant under gray value transformation	1. Intensive computation 2. Unable to capture shape aspects of tonal primitive 3. Not working well for texture with large-size primitive 4. May miss some valuable information in the undirected distance
Wavelet-preprocessed golden image subtraction	1. Easy to choose the size of golden image 2. Shortest time complexity among WGIS, DT and BB in implementation 3. Able to outline defective region after detection	Cannot detect defect near the borders
Direct thresholding	Haar wavelet transformed sub-images are lower resolution so that lower computational power in detection part.	Coarse in detection results
Bollinger bands	1. Simplicity : BB is built on the concept of moving average and standard deviation 2. Defects can be shown clearly in the final image 3. Applicable in on-loom machine	Cannot detect defect near the borders
Local binary patterns	1. LBP feature is rotational invariant, multi-scale, highly discriminative texture operator 2. Computational efficient to WGIS and BB 3. Able to outline defective region after detection	Cannot detect defect near the borders
Regular bands	1. Simplicity : RB is built on the concept of moving average and standard deviation 2. Only one parameter: Length of period 3. Crystal clean in final image 4. Applicable in on-loom machine	Cannot detect defect near the borders

7.1.3. Factors affecting a method

As can be seen in this paper, the performance of a fabric inspection system is determined by many factors. For example, the factors could include contrast between defects and texture appearance, consistency of texture background, resolution of images, alignment and distortion of images, size and shape of a defect, speed of an algorithm, illumination, and image acquisition techniques. A mature and successful method should take all these factors into account when it is being developed.

7.1.4. Non-motif-based vs. motif-based approach

The major limitation of non-motif-based approach is the lack of generality and reliability on other patterned textures. Most of them are texture oriented methods that have three problems: (a) only evaluated over a limited number of pattern groups, (b) only tested with limited samples, and (c) required to cross-reference other repetitive (lattice) units in the pattern. Comparatively, motif-based method acquires defect-free information from within a motif, of which the concept can be readily extended to other wallpaper groups.

Table 14
Strengths & weakness of defect detection of motif-based approach.

Strengths	Weakness
1. A generalized method applicable to 17 wallpaper groups 2. No ground truth image required 3. Invariant to slight distortion, quantization errors and misalignment of the input lattices	Cannot outline the defective shape at final result

7.2. Synergy in future research

7.2.1. A common reference database

Most research presented in this review has its own database whose size and quality vary substantially. It would be desirable to have a common reference database as a platform for performance evaluation and comparison in the future. It is preferred that such database covers all 17 wallpaper groups of patterned texture in order to evaluate the generality and reliability of a method.

7.2.2. Hybrid approach

Hybrid approaches appear to offer higher detection success rates, e.g., 98.59% in [129] and 99.4% in [20]. In this review, the generalized motif-based method possesses many merits (e.g., no cross-reference need, ability to localize small defects and tolerance of noise). We believe that the motif-based approach can be integrated with other approach(es) to offer a higher detection success rate.

7.2.3. Computation complexity

Only a few existing defect detection methods [39,61,98,103,116] have real-time implementation. Among these methods, none could offer detection success rates over 90% in real environment (except 94% in [39] for noise-free testing images). Much effort is required in the future to develop computationally efficient methods in order to apply them to real-time inspection scenarios.

7.2.4. Extension of the motif-based approach to the p1 group

Currently, the motif-based defect detection method does not tackle the patterned texture of the p1 group such as plain and twill fabrics. Given its potential, it would be worth the effort to extend its theory to cover the p1 group. This will complete the quest for a generalized defect detection method for detecting defects of all possible patterned or non-patterned texture in the world.

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Henry Y.T. Ngan received the B.Sc. degree in mathematics in 2001, the M. Phil. degree in 2005 and the Ph.D. degree in 2008 in electrical and electronic engineering at The University of Hong Kong, China. He is currently a research associate in the Laboratory for Intelligent Transportation Systems Research at HKU. He held visiting positions in C&C Innovation Research Laboratories, NEC, Japan and Carnegie Mellon CyLab, Carnegie Mellon University, U.S. at Kobe, Japan in 2008–2009. He worked in the Industrial Automated Research Laboratory of the Department of Electrical and Electronic Engineering at HKU. He was a visiting scholar at the Industrial Automated Laboratory, the University of British Columbia, Canada from March to June of 2006. His current research interests include social signal processing, human–computer interaction, visual surveillance, surface defect detection, image processing, machine intelligence, pattern recognition and computer vision. He is a member of the IEEE, the ACM and the IET.

Grantham K.H. Pang obtained his Ph.D. degree from the University of Cambridge in 1986. He was with the Department of Electrical and Computer Engineering, University of Waterloo, Canada, from 1986 to 1996. After that, he joined the Department of Electrical and Electronic Engineering at The University of Hong Kong as an Associate Professor. He has published more than 160 technical papers and has authored or co-authored six books. He has also obtained five U.S. patents. His research interests include machine vision for surface defect detection, video surveillance, expert systems for control system design, intelligent control and intelligent transportation systems. Dr. Pang is a Chartered Electrical Engineer, and a member of the IET, HKIE as well as a Senior Member of IEEE. Dr. Pang has acted as consultant to many local and international companies.

Nelson H.C. Yung received his B.Sc. and Ph.D. degrees from the University of Newcastle-Upon-Tyne. He was lecturer at the same university from 1985 to 1990. From 1990 to 1993, he worked as senior research scientist at the Department of Defense, Australia. He joined the University of Hong Kong in late 1993 as Associate Professor. He leads a research team in digital image processing and Intelligent Transportation Systems. He is the founding Director of the *Laboratory for Intelligent Transportation Systems Research* at HKU. Dr. Yung has co-authored six books and book chapters and has published over 160 journal and conference papers in the areas of digital image processing, parallel algorithms, visual traffic surveillance, autonomous vehicle navigation and learning algorithms. He has two patents and successfully transferred his research to a spin-off technology company. He regularly delivers talks/seminars to government departments, professional institutions, associations and commercial companies and gives interviews to local TV and press. He acts as consultant to a number of local and international companies. He regularly serves as expert witness for the Courts of the HKSAR.