

2. REVIEW OF LITERATURE

Patterned fabric defect detection is one of the most important phases in fabric production and is a vital step used to improve fabric quality. Methods used for this purpose, must design and use approaches that can increase accuracy and at the same time reduce complexity and cost. Because of improvement in image processing and pattern recognition, automatic fabric defect detection can present accurate, quick and reliable evaluation of textile products.

After a fabric image is acquired, it passes through a series of image processing processes. These processes use adequate and appropriate algorithms for performing many operations like image enhancement, restoration, segmentation, feature extraction and finally, defect detection. There are several techniques published, which discuss the influence of fabric defects on the commercial aspects of textile industry (Su *et al.*, 2010; Behera, 2009; Sengottuvelan *et al.*, 2008; Mitropoulos *et al.*, 1999; Dorrity *et al.*, 1995, 1996). Texture is one of the most important characteristics in identifying defects or flaws. It provides important information for recognition and interpolation. A variety of techniques for describing image texture have been proposed in the research literature. The past few decades have envisaged interesting surveys focused on automated fabric inspection and defect detection (Shanbhag *et al.*, 2012; Haindl *et al.*, 2007; Behera *et al.*, 2004; Truchetet and Laligant, 2004; Malamas *et al.*, 2003; Baykut *et al.*, 1998; Frank and Ding, 1997; Newman , 1995). All of these methods view defect detection as a texture analysis problem.

According to these surveys, initially, systems deployed for defect detection on solid color fabrics used threshold techniques. Later on, systems that can detect more complicated pattern fabric were introduced for both slanted pattern fabric and jeans (Srikaew *et al.*, 2011). Many methods have been proposed for fabric defect detection including statistical (Kumar and Pang,

2002a), spectra (Gonzalez and Woods, 2007), structural (Allen and Mills, 2004), Gabor filter (Escofet *et al.*, 1998b, Bodnarova *et al.*, 2002; Mak and Peng, 2006). These methods, as mentioned in Chapter 1, can be grouped as non-motif based method and motif-based method. This chapter presents some of the studies related to both these types. Figure 2.1 presents the categorization of the various techniques for defect detection in patterned fabrics.

2.1. NON-MOTIF-BASED METHODS

The methods proposed under non-motif categories can be grouped into six categories, namely, statistical, spectral, model-based, learning, structural and hybrid approaches. This section presents the various algorithms proposed under each of these groups.

2.1.1. Statistical Approaches

Statistical approaches measure spatial distribution of pixel values (Xie, 2008) to separate fabric image into regions of distinct statistical behavior. Here, the statistics of defect free regions are assumed to be stationary and other regions extend over a significant portion of fabric images. Based on the number of pixels defining the local features, Mahajen *et al.* (2009) classified statistical approaches as first, second and higher order statistics. First order statistics estimate properties like average and variance of individual pixel values and ignore spatial interaction between image pixels. The second and higher order statistics estimate properties of two or more pixels values occurring at specific locations relative to each other. The statistical approaches have been extensively applied in fabric detections and this section presents the most prominent algorithms. Frequently used methods under this category are auto-correlation function, co-occurrence matrices and fractal dimensions, using which the spatial distribution are defined (Jain *et al.*, 2000; Chen *et al.*, 1993).

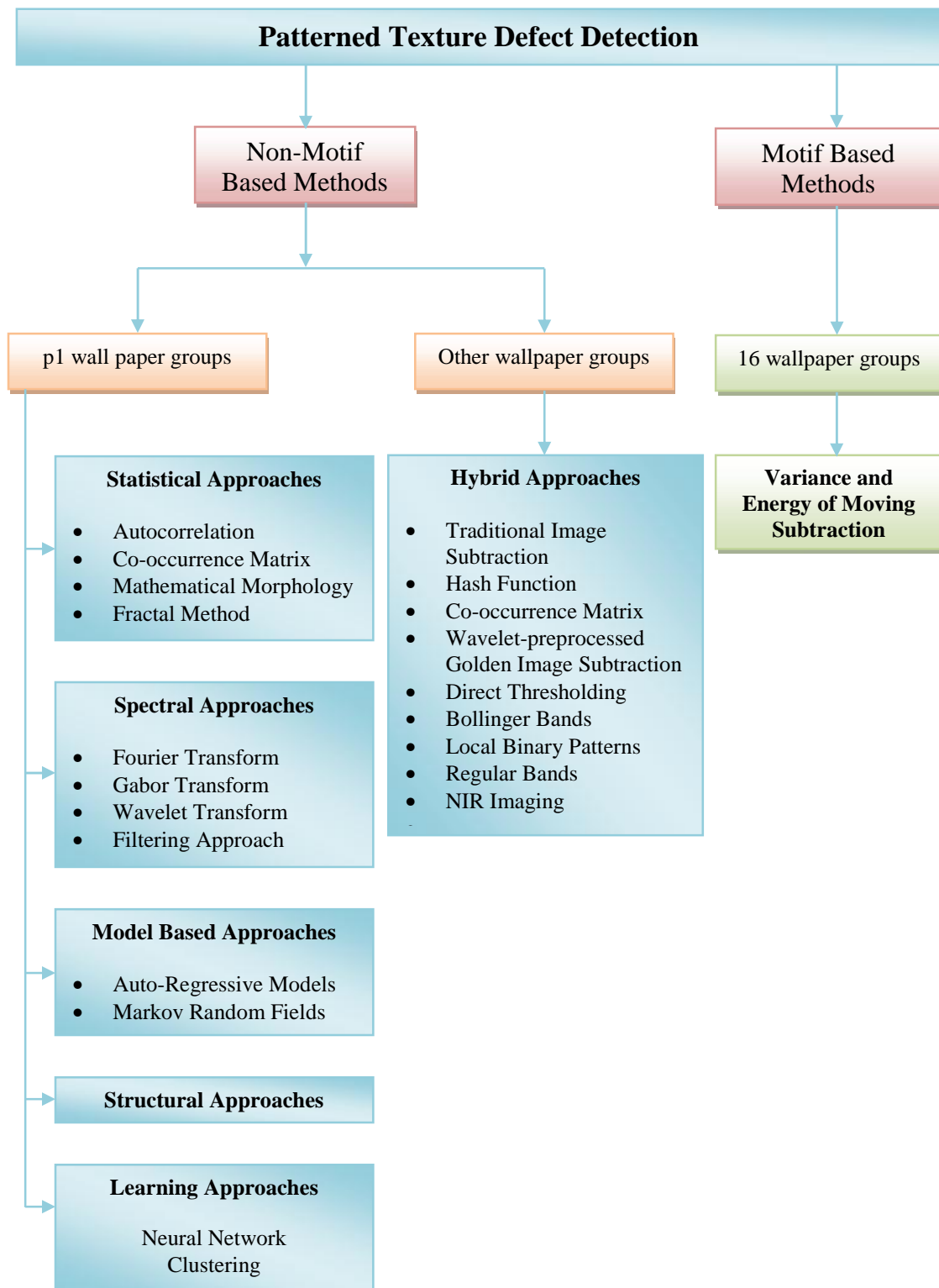


Figure 2.1 : Patterned Fabric Defect Detection Approaches

A) Auto-correlation Function

Automatic defect detection techniques for textured fabric images generally compute a set of textural features, in the spatial or spectral domains. This method is used to measure spatial frequency as second-order statistics to depict maxima at multiple locations corresponding to the length or width of the repetitive unit in a fabric image (Haralick, 1979). As the intensity maxima remain constant over a repetitive unit that is replicated in the patterned fabric, dramatic change in intensity maxima indicates a defect. This method has been used frequently on plain and twill fabric to identify defects. Autocorrelation method combines all parts of an image and is used to characterize repetitive structures. It measures the correlation between the image and its translated version with a displacement vector. It measure regular textures, exhibited as peaks and valleys. It is closely related to power spectrum of the Fourier Transform.

A two dimensional auto-correlation function was used by Wood (1990) to describe the symmetry (both translational and rotational) on carpet fabric image. The auto-correlation was used to calculate the period pattern length using a regularity approach proposed by Chetverikov and Hanbury (2002). The performance of the proposed method was compared with conventional morphological approach. The results showed that the proposed system misidentified defects when applied on fabric images with fine texture and required a reference frame of tonal primitive to analyze a texture.

Tolba and Abu-Rezeq (1997) applied a Self-Organizing Feature Map (SOFM) to detect and classify fabric defects. Initially, one-dimensional autocorrelation function was used to extract features. These features were immune to both continuous variations in the illumination intensity and noise as the result of the noise-rejection property of auto correlation function. In the next step, the two-point correlation function (Fatemi-Ghomi *et al.*, 1996) was used to compute the probability of finding difference in feature values for any randomly chosen pair of points within the feature space.

Recently, Hoseini *et al.* (2013) presented a novel method for segmenting defects from fabric images using autocorrelation function. The algorithm consisted of four steps. The first step calculated texture primitive template using autocorrelation function using defect free images. The second step enhanced the defect areas using difference method. The third step constructed mean image in order to reduce high frequency of background and finally the fourth step computed an automatic threshold to construct the binary image with defect pattern.

B) Co-occurrence Matrix

The co-occurrence matrix (CM) method, also known as the spatial gray-level dependence method, has been widely used in texture analysis and was proposed by Haralick *et al.* (1973). It 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.

Tsai *et al.* (1995) used this method to extract six features from twill fabric images and used Back Propagation Neural Network to detect defects. They reported 96% detection rate while testing with a small sized sample of 25 images consisting of 5 defect-free and 20 defective images. On the other hand, Latif-Amet *et al.* (1998, 2000) applied Sub-Band Co-Occurrence matrix (SBCM) on plain fabric images and reported 90.78% detection rate.

Siew *et al.* (1988) presented the assessment of carpet wear using Spatial Gray Level Dependence Matrix (SGLDM), neighboring Gray Level Dependence Matrix (GLDM), Gray Level Difference (GLD) method and the Gray Level Run Length Method. Also it has been applied to wood inspection (Connors *et al.*, 1983), surface defect detection (Iivarinen, 2000) and fabric defect detection (Tsai *et al.*, 1995). The original investigation into SGLDM features was pioneered by Haralick *et al.* (1973). Texture features, such as energy, contrast, entropy, correlation and homogeneity were then derived from the co-occurrence matrix. However only six of such features have been used for the defect

detection on wood and fabric defect detection has been shown with only two of these six features.

Iivarinen *et al.* (1996) applied co-occurrence texture features to detecting defects in paper web where the normal textures have characteristic frequency. Conners *et al.* (1983) have used six features of co-occurrence matrix, to identify nine different kinds of surface defect in wood.

Bodnarova *et al.* (1998) have examined this issue on the optimal displacement vector d for the fabric defect detection. The co-occurrence matrix features suffer from a number of difficulties. It appears there is no generally accepted solution for optimizing the displacement vector (Yang *et al.*, 2005; Monadjemi, 2004). The number of gray levels is usually reduced in order to keep the size of the co-occurrence matrix manageable. For a given displacement vector, a large number of features can be computed, which implies dedicated feature selection procedure. This technique can be computationally expensive for the demands of a real-time defect inspection system, but it have been exploited in many studies as accurate technique.

Recently, Mingde *et al.* (2012) presented a textural fabric defect detection method using adaptive quantized gray-level co-occurrence matrix and support vector description data.

From the various papers reviewed, a comparison of co-occurrence matrix method with auto-correlation method showed that the co-occurrence matrix to be invariant under monotonic gray value transformations and the spatial features to be superior to that of auto-correlation method (as the co-occurrence probabilities can extract more information in one spatial distance, which is the measure between two pixel locations). However, the co-occurrence matrix also has two main issues (Haralick, 1979). They show poor performance with textures constructed from large-sized primitive and they require intensive computations due to large number of adjacency pixels in calculation.

C) **Mathematical Morphology**

A non-linear approach called mathematical morphology (Serra, 1982) is the field of image analysis and processing to study regional shapes and is based on geometrical representation and description of an image. Morphological image processing has relevance to conditioning, labelling, grouping, extracting and matching operations on images (Vergados *et al.*, 2001). For examples, the morphological operations can filter out the periodic structure of fabric in the optical domain by inserting a Fourier lens after proper spatial filtering. As morphological operations are ideal tools for denoising, this technique has been exploited for noise removal in spatially filter images of fabrics. This method uses operations like erosion and dilation (Weeks, 1996) to smoothen, sharpen or noise removal to enhance an image. Several studies have used mathematical operations for fabric defect detection.

Mak *et al.* (2005) used this method to achieve a detection rate of 97.4% while tested on 78 (39 defect free and 39 defective) 256 x 256 sized plain and twill fabric images. The same authors extended their work to be tested 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 the results produced showed reliability, discussions on fabrics of other wallpaper groups were not provided.

The illumination and distance between camera and fabric were considered as two determining features for fault detection and was studied by Kwak *et al.* (2001). In their experiments, the distance was arbitrarily adjusted using a trial and error method. They developed an automatic vision detection system for automatic identification and classification of fabric defects on leather fabric. The defects were identified using a 2-step segmentation process based on thresholding and morphological processing.

Mallik-Goswami and Datta (2000) illuminated the inspected fabric by a collimated laser beam to obtain its diffraction pattern while the spatially filtered

noisy image is recorded by a CCD camera and converted to a binary one. The noise was then removed using morphological operations with a optimally selected structuring element.

Performance evaluation on the applicability of morphological approach for fabric defect detection was studied by Zhang and Bresee (1995). They presented detailed description on morphological operations for detection of fabric defects. The practical utility of this approach is limited, as most of the commonly occurring fabric defects will be missed by the simple thresholding operation. The results were compared with other statistical techniques like auto-correlation function, mean and standard deviations of sub-blocks of images. The results showed that morphological approach achieved 90.41% detection rate while the other statistical approaches obtained around 95.89%.

Alternatively, according to Mallick-Goswami and Datta (2000), detecting defects morphologically on spatially filtered images of fabrics produces better results, particularly when the fabric is fine and contains defect of small size. In their experiments the morphological operations are only performed on a periodic images defect, unlike Zhang and Bresee (1995) where the entire structure of thresholded fabric image was utilized.

Chetverikov and Hanbury (2002) compared the performance of regularity approach with the morphological approach for fabric detection and showed 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 above three studies concluded that morphological approach has the advantages of being sensitive to defect size and shape, work better for segmentation due to the effect of clustering and noise removal. They are more localized than the regularity approach and is, therefore, most appropriate on unidirectional texture. However, they do are not based on a single visual concept.

D) Fractal Methods

Fractal-based texture analysis was introduced by Pentland (1984). Voss (1986) refers to box counting as the process of estimating the probability that m points lie in the box. Keller *et al.* (1989) proposed a modification of method due to Voss, which presents satisfactory results up to Fractal Dimension (FD) = 2.75. According to Chen *et al.* (1993) and Mandelbrot (1982), fractal based systems are proficient and popular to model the statistical qualities like roughness and self-similarity on many natural surfaces. Chaudhuri and Sarkar (1992) proved that fractals as an efficient approach to compute fractal dimension in texture image

Initially, the applicability of fractals was tested by Kaneko (1989), who used fractals to classify 65 anonymous texture samples from the Brodatz Texture Database (2010) and achieved an accuracy of 93.85%. This study motivated several other authors on the use of fractals for defect detection (Kasparis *et al.*, 1995; Chenoweth *et al.*, 1995). Kasparis *et al.* (1995) performed a performance evaluation of these three techniques and reported fractals to be computationally demanding even with noise-free texture samples.

Another leading method, proposed by Conci and Proenca (1998), is a fractal image analysis system using a differential box-counting approach and used the differences in computing non-overlapping copies of a set of images during fabric defection. The method gave satisfactory results in all ranges of fractal dimension 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 another set has 80 images. From their experience, a quality and consistent image acquisition and lighting, are the two major challenges.

Recently, Bu *et al.* (2009) compared their proposed multiple fractal based system with single fractal feature using four fractal features and support vector data description. The system 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%.

From the various studies published on the usage of fractal dimension for discriminating texture defective areas, it has been found that this method does not cover all possible fractal dimension ranges for textiles and therefore, is not applicable to many types of textiles. Moreover, these methods show poor efficiency and high false alarm rate (Monadjemi, 2004).

2.1.2. Spectral Approaches

Spectral based algorithms are robust and efficient computer-vision approaches for fabric defect detection. In these approaches, texture is characterized by texture primitives or texture elements and the spatial arrangement of these primitives (Vilnrotter *et al.*, 1986). Thus, the primary goals of these approaches are firstly to extract texture primitives and secondly to model or generalise the spatial placement rules. The high degree of periodicity of basic texture primitives, such as yarns in the case of textile fabric, permits the usage of spectral features for the detection of defects. However, random textured images cannot be described in terms of primitives and displacement rules as the distribution of gray levels in such images is rather stochastic. Thus, spectral approaches are not suitable for the detection of defects in random texture materials.

Various approaches for the detection of defects in uniform textured material using frequency and spatial- frequency domain features have been reported in the literature. In spectral- domain approaches, the texture features are generally derived from the Fourier Transform (FT), Gabor Transform (GT), Wavelet Transform (WT) and filtering approaches. This section covers some of the studies in these four topics.

A) Fourier Transforms

Fourier transforms are derived from the Fourier series (MathWorld, 2010). The spatial domain is usually noise sensitive and arduous to locate defects while FT utilizes the frequency domain to characterize the defects. The FT has the desirable properties of noise immunity and enhancement of periodic

features. The FT characterizes the textured image in terms of frequency components. The periodically occurring features can be observed from the magnitude of frequency components. These global texture patterns are easily distinguishable as concentration of high-energy bursts in the spectrum.

The Fourier transform of textile fabric can also be obtained in optical domain by using lenses and spatial filters. The fabric defect detection system using the measurements of the first-order and the zero-order intensities have been developed (Mead *et al.*, 1978; Ribolzi *et al.*, 1993; Ciamberlini *et al.*, 1996a).

Wood (1990) 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.* (1996) for plain cotton fabric to detect and identify the defects on an on-loom neural network based inspection machine.

Casterllini *et al.* (1996) and Ciamberlini *et al.* (1996a) used the same for cotton and wool woven fabrics and 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. Similar study was also performed by Campbell *et al.* (1998a, 1998b) for woven denim (twill) fabrics.

Liu and Jernigan (1990) reviewed a set of 28 textural features extracted in the Fourier spectrum for texture analysis. Escofet *et al.* (1998a) used the angular correlation of the Fourier spectra to evaluate fabric web resistance to abrasion. Ciamberlini *et al.* (1996b) have described the design of spatial filters: a fixed

filter adaptable for different types of fabric and a universal spatial filter for the detection of defects in textured materials. Campbell and Murtagh (1998) have detailed a Windowed Fourier transform based method to detect defect on denim fabric samples.

According to Tsai and Hsieh (1999) and Tsai and Huang (2003), an inverse FT can remove the line patterns as well as periodic and repetitive patterns of any statistical texture. Tsai and Hsieh (1999) used the Fourier transform to reconstruct textile images for the defect detection. The line patterns in the textile images, supposed to be defects, were taken out by removing high energy frequency components in the Fourier domain using a one dimensional Hough transforms. The difference between the restored image and the original image were considered as potential defects. A similar idea was explored by Tsai and Huang (2003), but low pass filtering was used to remove the periodic information.

Chan and Pang (2000) 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, were proposed for improvement.

Chiu *et al.* (2002), 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.

Later, Sengottuvelan *et al.* (2008), used an approach based on Fourier transform to detect the various types of fabric defects. The central spatial frequency spectrum is used, from which seven significant characteristic parameters are extracted for detecting the type of defect. Further, they carried

out experiments to detect only two classes of defects namely double yarn and missing yarn which are found to be consistent in a number of samples.

B) Gabor Transform

The general form of Gabor function 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 (Kumar and Pang, 2002b). On the other hand, the Fourier transform is an analysis of the global frequency content in the signal, it is not able to localize the defective regions in the spatial dependency into Fourier analysis is through the windowed Fourier transform. If the window function is Gaussian, the windowed Fourier transform becomes the well known Gabor transform, which can achieve optimal localization in the spatial and frequency domain (Daugman, 1980).

There exist two categories of implementations of Gabor filters (Mak and Peng, 2008; Bodnarova *et al.*, 2002):

- (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 that use fewer filters, but a correct choice is hard and crucial.

Previously, Jain and Farrokhnia (1991) used it in segmentation and classification of textures with dyadic coverage of the radial spatial frequency range. The Gabor filter bank has been extensively studied in visual inspection. Kumar and Pang (2000) perform fabric defect detection using only real Gabor functions. Later, Kumar and Pang (2002b), they used a class of self similar Gabor functions to classify fabric defects. They also investigated defect detection using only imaginary Gabor functions as an edge detector.

Bodnarova *et al.* (2002) applied a Fisher cost function to select a subset of Gabor functions based on the mean and standard deviation of the template feature images to perform textile flaw detection. Tsai and Hsieh (1999), Tsai and Huang (2003), Tsai and Hsiao (2001) and Tsai and Chiang (2003) suggested that a single 2D GF approach by Tsai and Wu (2000) and a one dimensional GF approach was proposed by Tsai and Lin (2002). For the latter, computational complexity is significantly decreased from 2D to 1D in Gabor space.

At the same time, Ding *et al.* (2002) 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 Tsai and Wu (2000), Bodnarova *et al.* (2000, 2002) proposed optimal 2D GF for defect detection and achieved an accuracy of 82.86%.

An on-loom inspection has been proposed for homogenous fabric based on the energy response from the convolution of GF banks in frequency and orientation domains (Shu and Tan, 2004). They detailed a method of detecting the fabric defects automatically based on multi-channel and multi-scale Gabor filtering. Experiments on various simulated defect fabric images have shown the effectiveness of this method. This method has accurate location and fine detection of fabric defects.

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 (2002c) 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 proposed by Jain and Farrokhnia (1991) and 3rd (web inspection) schemes.

Bennamoun and Bodnarova (2003) applied six standard techniques on non-patterned fabric defect detection and tried to apply an optimized Gabor filter on jacquard fabric inspection. However, only two different jacquard samples,

with holes and smash flaws, respectively, were investigated under their Gabor filtering techniques. The detection results in that paper showed parts of the defective regions on original images and there is no strong evidence that the Gabor filter will be effective enough on other kinds of defects existing in those two kinds of patterned jacquard fabric.

Farooq *et al.* (2004) developed a mechatronic methodology to detect lace defects using a visual feedback approach. They claimed the system could adjust image rotation, scale and translation parameters in a feedback control mode. After alignment process, both the reference image and the test image used subtraction method for fault prediction.

Hou and Parker (2005) investigated a method for detecting defects on textured surfaces using a Support Vector Machines (SVM) classification approach with Gabor wavelet features. Instead of using all the filters in the Gabor wavelets, an adaptive filter selection scheme is applied to reduce the computational cost on feature extraction while keeping a reasonable detection rate. Their experimental result shows, this method can successfully detect and segment defects in texture images.

Gabor wavelet transform is applied to detect the defects in fabrics (Arivazhagan *et al.*, 2006). Gabor filter scheme that imitates the early human vision process is applied to the sample under construction. The result obtained by proper thresholding ensures segmentation of the defect, which in turn confirms efficiency of this method.

Liu *et al.* (2008) 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 (2006) proposed an optimal individual filter, from a set of Gabor wavelet filters, with a similar 1st scheme to that of the method proposed by Kumar and Pang (2002b). Ogata *et al.* (2005) 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.

Recently, Li *et al.* (2009) 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 (2008) 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 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).

Han and Zhang (2009) proposed a fabric defect detection method based on Gabor filter masks. The performance is evaluated off-line by using a group of fabric sample images containing many kinds of fabric defects. Their experimental result shows accurate defect detection with low false alarms.

The main weaknesses of the techniques discussed above are the limited testing samples, where their reliability on a larger dataset is still an open question.

C) Wavelet Transforms (WT)

Wavelet representation Mallat (1989) is a theory for multi-resolution signal decomposition. As the basis functions of FT are sinusoids, wavelet transforms 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. In the recent past, multiresolution decomposition schemes based on wavelet transform

have received considerable attention as alternatives for the extraction of textural features. The multiresolution wavelet representation allows an image to be decomposed into a hierarchy of localized subimages at different spatial frequencies. It divides the 2D frequency spectrum of an image into a low pass (smooth) sub image and a set of high pass (detail) subimages. The textural features are then extracted from the decomposed subimages in different frequency channels and at different resolution levels.

For plain and twill fabrics defect detection, WT is commonly used for feature extraction. Other previous WT approaches include Fuzzy Wavelet Analysis (Mufti and Vachtsevanos, 1995), multiscale wavelet method (Lambert and Bock, 1997), WT image restoration schemes (Tsai and Hsiao, 2001; Tsai and Chiang, 2003) and adaptive level-selecting scheme to analyze the CMs from approximated sub-images (Han and Shi, 2007). Detection success rates of these methods ranged from 98% to 100%. The main problem of these methods was that their reliability was not known due to limited number of samples test.

Karayiannis *et al.* (1999) 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 was proposed by Sari-Sarraf and Goddard (1999; 1998) 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 when compared to other methods.

In general, wavelet basis is heuristically selected to capture the most outstanding features of defects. Yang *et al.* (2002b) 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. The system 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 same authors (Yang *et al.*, 2004), 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 their previous work.

Scharcanski (2005) used the Discrete Wavelet Transform (DWT) to classify stochastic textile texture. Rather using fixed scales, Kim *et al.* (1999) employed a learning process to choose the wavelet scales for maximizing the defect ability of fabric defects. Latif-Amet *et al.* (2000) extracted co-occurrence and MRF-based features from wavelet transform coefficients for fabric defect detection. Gray level difference-based features from sub bands of the wavelet transform were also applied in classifying fabric defects.

Jasper *et al.* (1996, 2004) have detailed the design of a texture specific wavelet basis filter, which can be tuned to a particular texture. The design of adaptive orthonormal wavelet bases has been shown to achieve the best performance in the characterization of fabric defects (Yang *et al.*, 2004). Later, the same authors detailed the adaptive wavelet-based methodology from the use of a single adaptive wavelet to multiple adaptive wavelets. For each class of fabric defect, a defect – specific adaptive wavelet was designed to enhance the

defect region at one channel of the wavelet transform, where the defect region can be detected by using a simple threshold classifier. This multiple adaptive wavelets method has been evaluated on the inspection of 56 images containing eight classes of fabric defects and 64 images without defects, where 98.2% detection rate and 1.5% false alarm rate were achieved in defect detection.

The detection of fabric defects using wavelet packet decomposition and Independent Component Analysis has been investigated by Serdaroglu *et al.* (2006). Kumar and Gupta (2000) have used mean and variance of “Haar” wavelet coefficient for the identification of surface defects. The fabric texture can also be considered as noise and removed using wavelet shrinkage.

Recently, Truchetet and Laligant (2008) gave a detailed review on wavelet analysis in industrial application. In the same year, Guan *et al.* (2008) presented a new defect detection method based on wavelet characteristics. The detail signal feature after wavelet decomposition of fabric image is extracted and it is compared with the detail signal feature of normal fabric image decomposition to determine fabric defects. Their experimental result shows the defect detection accuracy is over 92.5%.

An extracted sub-image features approach based on wavelet transition with one resolution level and Fourier transform is presented by Guan and Shi (2008). By using restoration scheme of the Fourier transform, the normal fabric textures of smooth sub-image in the spatial domain are removed by detecting the high energy frequency components of sub-image in the Fourier domain, setting them to zero using frequency-domain filter and back-transforming to a spatial domain sub-image. Then, the smooth and detail sub-images are segmented into many sub-windows, in which standard deviation are calculated as extracted features. These extracted features are compared with normal sub-windows features to determine whether there exists defect.

D) Filtering Approach

Filtering is utilized in many applications (e.g. image enhancement) and is applied between an image neighborhood and a filtering mask (Chen *et al.*, 1993). Two kinds of filtering methods in general use are :

- (1) frequency domain filtering based on Fourier transform
- (2) spatial filtering based on direct operations on image pixels.

Both are sensitive to noise in the image (Yang, 2003). Neubauer (1992) recommended a defect segmentation method based on multiple linear filters (including three separable convolution filters as first 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 was utilized to detect defects on raw fabrics (Meylani *et al.*, 1996a, 1996b).

To reduce the computation complexity for detection, a Multi-Scale Differentiation Filtering (MSDF) method was suggested by Zeng and Hirata (2002) 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 was effective to detect different defects with a high sensitivity. Yet, it produced distorted output for large-scale defects.

E) Miscellaneous Approaches

Saeidi *et al.*, (2005) described a computer vision-based fabric inspection system implemented on a circular knitting machine to inspect the fabric under construction. The detection of defects in knitted fabric was performed and the performance of three different spectral methods, namely, the discrete Fourier transform, the wavelet and the Gabor transforms were evaluated off-line. Knitted fabric defect-detection and classification was implemented on-line. The captured images were subjected to a defect-detection algorithm, which was based on the

concepts of the Gabor wavelet transform and a neural network as a classifier. An operator encountering defects also evaluated the performance of the system. The fabric images were broadly classified into seven main categories as well as seven combined defects. The results of the designed system were compared with those of human vision.

Some fabric defects that produce very subtle intensity transitions may be difficult to detect using above-mentioned spectral approaches. A potential solution to detect such defects is to employ optimal Finite Impulse Response (FIR) filters. A FIR filter has generally more free parameters than a Gabor filter and thus offers added advantage of computational ease. Therefore, it offers a large feature separation between the defect-free and the defective regions of the filtered image. The advantage of FIR filters is that they can implement any impulse response, provided it is of finite length.

Kumar (2008) emphasized on smaller spatial masks, as compared to those from optimal Gabor filters and demonstrated fabric defect segmentation with optimal FIR filters as small as 3×3 or 5×5 mask size. Also, Kumar and Pang (2002b) proposed a linear FIR filter with an optimized energy separation. They investigated the approach performance with the size variation of both optimal and smoothing filters. They concluded that the size of optimal filter has appreciable effect on the performance for the defect detection. These filters can be used to supplement the performance of the existing inspection systems that fail to detect a class of specific defects.

The Wigner distribution function is Fourier-like but offers better co-joint resolution than Gabor or difference of Gaussians for co-joint spatial and spatial-frequency image representation. This algorithm is effective when implemented for online fabric defect detection but its computation time is prohibitive. However its utility for unsupervised fabric inspection, in simultaneously detecting defects from a large number of classes, is yet to be demonstrated. The major drawback of these techniques is the presence of interference terms between the different components of the image.

2.1.3. Model-Based Approach

A random field (Jain, 2002) 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. Model-based texture analysis methods are based on the construction of an image model that can be used not only to describe texture, but also to synthesize it. Model-based approaches are particularly suitable for fabric images with stochastic surface variations (possibly due to fiber heap or noise) or for randomly textured fabrics for which the statistical and spectral approaches have not yet shown their utility. The model parameters capture the essential perceived qualities of texture. MRF have been popular for modeling images. MRF theory provides a convenient and consistent way for modelling context dependent entities such as pixels, through characterizing mutual influences among such entities using condition MRF distribution (Li, 2001).

A) AutoRegressive Model

AR model (Haralick, 1979) exploits the linear dependence between different pixels of a textural image. It can capture any textural feature and characterize the texture. Serafim (1991, 1992) proposed a 2D AR model for feature representation and cooperation with multi-resolution pyramids of natural surface classification and leather defect segmentation. The AR model approach proposed by Serafim (1991, 1992) was sensitive to very small width defects and easily affected by the lighting due to similarity between the defects and leather background.

Basu and Lin (1992) 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 computationally fast and efficient. A 1D AR method was used by Hajimowlana *et al.* (1998) for web inspection using a CCD camera as real-time defect detection, with successful testing on a defective plain fabric and some synthesized textural images. The method was insensitive to the translation of pattern on texture.

B) Markov Random Fields

MRF (Kendall and Snell, 1980) can be applied in many image processing areas; texture segmentation (Wilson and Li, 2003; Marroquin *et al.*, 2003) and classification (Deng and Clausi, 2004; Wang and Liu, 1999). It can combine both statistical and structural information (Cai and Liu, 2002) in pattern recognition. Its principle stresses that pixel intensity in an image depends on the neighboring pixels only.

Cohen *et al.* (1991) utilized Gaussian MRF (GMRF) to model defect-free texture on fabric images and showed that the GMRF model 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.

Campbell *et al.* (1996) detects an alignment pattern in preprocessed images via model based clustering and uses an approximate Bayes factor to assess the evidence for the presence of a defect. In the same year, Ozdemir and Ercil (1996) suggested applying a MRF model in fabric 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 of fair quality, the MRF approach (0.33 seconds) outperformed the KL approach (3.13 seconds) in execution times.

Brzakovic *et al.* (1997, 1995) discuss a theoretical approach based on a Poisson model for inspection of web materials. The inspection objective is to

quantify the randomness and homogeneity across the material. Baykut *et al.* (2000) implemented this method in a real-time application with a dedicated DSP system. Ozdemir *et al.* (1998) showed that MRF based methods were competitive in a comparative study against other statistical and spectral based methods in defect detection.

Though MRF models captured local spatial contextual information in an image, feature extraction was weak at identifying small defects on fabric according to Yang (2003). Chan *et al.* (2005) proposed a wavelet-domain Hidden Markov Tree model with a level set segmentation technique, but no detailed evaluation was given.

2.1.4. Structural Approaches

Structural Approach (SA) usually considers the texture as a composition of texture primitives. These primitives can be as simple as individual pixels, or a region with uniform gray levels, or line segments. Consequently, the main objectives of these approaches are

- (i) to extract texture primitives
- (ii) to model or generalize the spatial placement rules.

The placement rules can be obtained through modeling geometric relationships between primitives or learning statistical properties from texture primitives (Xie, 2008; Mahajan *et al.*, 2009). Structural texture analysis mainly composes of two steps: extraction of texture elements and inference of the placement rule. The usual criticism of SA is that it only performs well on very regular texture (Chen *et al.*, 1993).

Chen and Jain (1988) 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 (1998) 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.

Later, this method was modified as Maximum Frequency Difference (MFD) (Bennamoun *et al.*, 1998) and 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 using the technique proposed by Chetverikov (2000a, 2000b).

However, these approaches were not successful on fabric defect detection, mainly due to the stochastic variations in the fabric structure (due to elasticity of yarns, noise, fiber heap, fabric motion, etc.) which cause severe problems in the extraction of texture primitives from the real fabric samples. Moreover, the following two drawbacks of structural defects also exist.

- (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 two period length of the pattern structure.

2.1.5. Learning Approaches

Learning based approaches can be grouped into two, namely, supervised learning (classification) and unsupervised learning (clustering). Both the methods differ only in the structure of modeling. The problem of unsupervised learning is to hidden structure or analyze for knowledge in unlabeled data,

whereas supervised learning infers knowledge from labeled training data. Both techniques have been found to be used with fabric defect detection and this section presents some of these published reports.

A) Supervised Learning

Usage of Neural Network (NN) models (Jain *et al.*, 2000; Haykin, 1999) for fabric detection and classification have attracted several scientists. It employ organization principles (e.g., learning, or generalization) and can perform many tasks such as feature extraction, segmentation and optimization (Egmont-Petersen *et al.*, 2002). They are one of the fastest and most flexible classifier used for fault detection due to their non-parametric nature and ability to describe complex decision regions. Its limitations include its black-box character, difficulty in coping with abundance of features and associated variations in scale, position and orientation.

Initially, Li *et al.* (1997) and Sandy *et al.* (1995) used a subtraction method, which was previously applied in Printed Circuit Boards (PCBs) by Chin and Harlow (1982) for defect detection on lace, which is one kind of patterned fabric with a fine and sophisticated pattern of threads. This subtraction method is equivalent to an Exclusive-OR (XOR) operation. In detection, the testing lace sample was subtracted by a prototype version of the same pattern while the repeat distance of the pattern on the testing lace sample was found by autocorrelation. Thresholding was then used along with a neural network to detect and classify the different kinds of defects. This subtraction method was classified as traditional, which is not the same as the golden image subtraction method mentioned below. The main weakness of this traditional subtraction method is the alignment problem between the reference image and test image.

Hu and Tsai (2000) proposed a method using best wavelet packet bases and Artificial Neural Network (ANN) for detecting four types of defects fabrics. From the wavelet packet base tree, the smallest six entropy values and positions were extracted and used as features for training and testing ANN to identify

fabric defects. The system was analyzed with three considerations for improving the classification rate of fabric defect detection system. The parameters considered are maximum with different number of resolution levels, differently scaled fabric images and vanishing moments. The experimental results showed that the total classification rate for a wavelet function with a maximum vanishing moment of four and three resolution levels produced maximum percentage and differently scaled fabric images had no obvious effect on the classification rate.

Shiau *et al.* (2000) constructed a back-propagation neural network topology to automatically recognize neps and trash in a web by color image processing. With a back-propagation neural network, the RGB (red, green and blue) values corresponding with the image pixels were used to perform the recognition and three categories (i.e., normal web, nep and trash) were recognized to determine the numbers and areas of defection regions both neps and trash. According to experimental analysis, the recognition rate reached to 99.63% under circumstances in which the neural network topology is 3-3-3.

Choi *et al.* (2001) developed a new method for a fabric defect identification system by using fuzzy inference in multi-conditions. The system has applied fuzzy inference rules and the membership function for these rules to adopt a neural network approach. Only a small number of fuzzy inference rules were required to make the identifications of non-defect, slub (warp direction), slub (weft direction), nep and composite defect. One fuzzy inference rule can replace many crisp rules. This system can be used to design a reliable system for identifying fabric defects. Experimental results with this approach have demonstrated the identification ability which was comparable to that of a human inspector.

Huang and Chen (2001) investigated an image classification by a neural-fuzzy system for normal fabrics and eight kinds of fabric defects. This system combined the fuzzification technique with fuzzy logic and a back-propagation learning algorithm with neural networks. Four inputs featured the ratio of

projection lengths in the horizontal and vertical directions, the gray-level mean and standard deviation of the image and the Large Number Emphasis (LNE) based on the neighboring gray level dependence matrix for the defect area. The neural network was also implemented and compared with the neural-fuzzy system. The results demonstrated that the neural-fuzzy system was superior to the neural network in classification ability.

A compact fabric inspection system using neural network was presented by Rohrmus (2000) but is not adequately detailed. An analogous work for texture defect detection using cellular neural networks is detailed in Occhipinti *et al.* (2001). The FFNN (Feed Forward Neural Network) and SVM (Support Vector Machine) require training from the known classes of fabric defects. Huang and Chen (2001) have used back propagation neural network, with fuzzy logic, to achieve the classification of eight different kinds of fabric defects along with defect-free fabric.

Stojanovic *et al.* (2001) 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 FFNN architecture based on principal component analysis (PCA) was proposed by Kumar (2003). A three-layer Back Propagation Neural Network (BPNN) was proposed by Kuo *et al.* (2003a) for plain white fabric defect detection. 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 architecture of BPNN was presented by Kuo *et al.* (2003b) 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.

Kumar and Shen (2002) investigated two methods for the detection of defects on textured surfaces using neural networks and SVM. Results showed that the real-time implementation of defect segmentation scheme using FFN was

computationally costly. Although the real time computational complexity of SVM is also similar, they do not suffer from the problem of local minimum and therefore were computationally simple to train.

Shady *et al.*, (2006) developed a new method for knitted fabric defect detection and classification using image analysis and neural networks. Images of six different induced defects (broken needle, fly, hole, barré, thick and thin yarn) were used in the analysis. In the same period, Elaleem *et al.* (2006) proposed an automated visual inspection system using Adaptive Neural Fuzzy Inference System (ANFIS) that can detect and classify knitting machine fabric defects.

Castilho *et al.* (2007) presented a real-time fabric defect detection based intelligent techniques. Neural Networks (NN), Fuzzy Modeling (FM) based on product-space fuzzy clustering and ANFIS were used to obtain a clearly classification for defect detection. Experimental results for real fabric defect detection, shows the usefulness of the three intelligent techniques and they further stated that NN has a faster performance. Online implementation of the algorithms showed they can be easily implemented and may be adapted to industrial applications without great efforts.

Yin *et al.* (2009) proposed yet another architecture of BPNN which accomplished around 91% and 100% detection success rates for hole (16 images) and oil stain (16 images) of twill fabric, respectively. Though the detection accuracies of all these systems were high, the image sampling quality was poor and the reliability was unknown.

Yuen *et al.* (2009b) explored a novel method to detect the fabric defect automatically with a segmented window technique which was presented to segment an image for a three layer BP neural network to classify fabric stitching defects. This method was specifically designed for evaluating fabric stitches or seams of semi-finished and finished garments. Nine characteristic variables were obtained from the segmented images and input into a BPNN for classification and recognition. The classification results demonstrated that the inspection

method developed was effective in identifying the three classes of knitted-fabric stitching.

Yuen *et al.* (2009a) presented a novel hybrid model through integration of Genetic Algorithm (GA) and neural network to classify the type of garment defects. They developed a segmented window technique to segment images into several classes using monochrome single loop rib work of knitted garment. Four types of feature characteristics were extracted and were used as input to a BPNN to classify the sample images. Their experimental result shows very high accuracy rate of recognition and thus provides decision support in defect classification.

Shi *et al.* (2009) describes an adaptive image-segmentation method based on a simplified Pulse-Coupled Neural Network (PCNN) for detecting fabric defects. They introduce a new parameter called the Deviation Of Contrast (DOC) to describe the contrast difference in row and column between the analyzed image and a defect-free image of the same fabric. The simplification of PCNN reduces the number of the network parameters by utilizing the local and global DOC information for the parameter selections.

Recently, radial basis function method proposed by Zhang *et al.* (2010), using the same feature extraction masks of Kumar (2003), achieved 83.4% defect classification for 270 images.

B) Unsupervised Approaches

Chen (2006) utilized a color scanner to digitalize the gray-level images of solid woven fabrics. The enhanced images were then obtained after a morphological operation and the warp and weft crossed areas can be located based on the interlacing points. Four texture types in these areas were featured using the first-order and the second-order statistics method and then classified by a Fuzzy C-Means (FCM) clustering method. The results were demonstrated that three basic weave patterns can be identified correctly.

Similar methods have been reported and applied in the references (Kuo *et al.*, 2004; Pan *et al.*, 2010a). Besides, a new method based on the particle swarm optimization algorithm for weave pattern recognition was presented by Chen and Tu (2010). A digital microscope was used to capture the fabric images. After a series of image pre-processing, such as histogram equalization, binarization and denoising, the characteristics of the fabric construction can be extracted by the width method with warp, weft and the particle swarm optimization was then used to identify the weave patterns.

2.2. HYBRID APPROACHES

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 (Sandy *et al.*, 1995, Farooq *et al.*, 2004; Yazdi and King, 1998; Tao *et al.*, 1997) and Jacquard fabrics (Ngan *et al.*, 2005; Baykal *et al.*, 2002a; Kuo and Su, 2003; Ngan and Pang, 2006, 2007, 2009; Tajeripour *et al.*, 2008). The methods used could be broadly classified as (i) template-matching approach and (ii) statistical and spectral approach, which are termed hybrid approach.

A) 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 of Chin and Harlow (1982)). TIS subtracts a test image from a perfect master image and works perfectly if the input image is precisely aligned.

Sandy *et al.* (1995) 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.* (1997) proposed a similar subtraction approach, whereas Yazdi and King (1998) and Farooq *et al.* (2004) proposed a mechatronic approach for perfect alignment. TIS was very sensitive to noise and was found to be unsuccessful in a preliminary test (Ngan *et al.*, 2005).

B) Statistical and Spectral Approaches

Many methods fall under this category. Some examples include gray level thresholding method, normalized cross-correlation method, statistical moments approach, multilevel thresholding method, histogram properties approach, rank-order functions approach, fractal dimensions, edge detection based approaches, morphological operations approach and co-occurrence matrix function approach.

A gray relational analysis on co-occurrence matrix features was used by Kuo and Su (2003) 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 defective patterned textures, is a one dimensional approach that is sensitive to small changes in pattern. Four types of Hash functions were studied by Baykal *et al.* (2002b) and Baykal and Jullien (2002a) to detect defects from simple to complex textures.

The Direct Thresholding (DT) (spectral approach) obtained good Haar wavelet sub-images in the horizontal and vertical directions for detection was proposed by Ngan and Pang (2007) and Ngan *et al.* (2005). These systems achieved around 88.3% detection accuracy.

The Bollinger Bands (BB) method, originally for financial technical analysis (Bollinger, 2002), was based on moving average and standard deviation. It was extended from a 1D approach into a 2D approach for Jacquard fabric inspection (Ngan and Pang, 2006; 2003). 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

computationally fast. However, one of its weaknesses was on detecting defects with slight color difference from texture pattern.

Local Binary Pattern (LBP) feature (Ngan *et al.*, 2003), 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 the proposal of Ngan and Pang, 2006). 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.

Texture properties can be extracted by using several bidimensional transform such as Discrete Cosine Transform (DCT), Discrete Sine Transform (DST), Discrete Hadamard Transform (DHT), Karhunen-Loeve Transform (KLT) and eigenfiltering. Unser (1986) tested different local linear transforms for texture classification and found KLT as the best algorithm. Also Ade *et al.* (1984) compared Laws filters, KLT, DCT and DHT for textile defect detection. In their experiments, the KLT performance, particularly on larger window size, was amongst the best.

Neubauer (1992) has detected fabric defect using texture energy features from low mask on 10×10 windows of inspection images. In his approach, three 5×5 Laws masks corresponding to ripple, edge and weave features (David, 1997) are used to extract histogram features from every window of the image. These features are then used for the classification of the corresponding window into defect-free or defect class, using a three-layer neural network.

Using eigenvalues of covariance matrix as a feature Ozdemir and Ercil (1996) have implemented fabric defect detection using an approach which is a variation of the KLT or eigenfilters method. A novel scheme of characterizing and classifying defects in woven textile fabrics has been attempted by Behra and Mani (2007). This back propagation based neural network coupled with the DCT

technique can lead to outstanding results for classification of various fabric defects. In online fabric inspection, the local transforms such as DCT or DST could be preferable to eigenfilters or KLT, since DCT or DST can be directly obtained from the camera using commercially available chips that perform fast and efficient DCT or DST transforms.

The Regular Bands (RB) method (Ngan and Pang, 2009) 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 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 and its theoretical design. The testing database had 166 images sized 256×256 from three types of fabrics (same as the BB method) in good quality.

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 requires the knowledge of the period length of a repetitive pattern.

On the other hand, a minority approach such as Near-InfraRed (NIR) method proposed by Millan and Escofet (2004) was a hardware approach to utilize NIR illumination instead of the traditional visible light source. In this system, 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.

Dhivya *et al.* (2013) presented a hybrid approach combining wavelet transformation and GLCM (Gray Level Co-occurrence Matrix) texture features. The wavelets were used to decompose the image into sub-bands and then GLCM features were extracted. This method reduces computation time and resources required. Euclidean distance was used as metric to classify the fabric image as defect free or not.

2.3. MOTIF-BASED METHODS FOR 16 WALLPAPER GROUPS

A generalized motif-based defect detection method (Ngan *et al.*, 2008, 2010a) 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. 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. It achieved a promising detection success rate of 93.86%. 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) (Ngan *et al.*, 2010b) 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.

2.4. MISCELLANEOUS APPROACHES

Apart from the above discussed methods, several other methods also exist for detecting defects in p1 group fabrics. For instance, the most recent method from Semnani and Ghayoor (2009) dealt with one specified defect, pills, in cotton fabric surface and utilized thresholding on histogram equalized images.

A spectral approach using Radon transform was applied by Aguilar *et al.* (2004) for unknown fabric. A PCA method Liu and Ju (2008) 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.* (2008) proposed a Gaussian mixture model with Expectation-Maximization to detect one specific kind of defect, oil (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 oils under four categories of laundering treatments. Regarding repeatability and reproducibility of the scheme, it was also verified under various scanners and different light intensities.

Another important method uses the edges of an image during defect detection. Edges can be detected either as micro edges using small edge operator masks or as macro edges using large masks (Davis and Mitiche, 1980). The distribution of amount of edges per unit area is an important feature in the textured images. The amount of gray level transitions in the fabric image can represent line, edges, spots, ripples and other spatial discontinuities. These features are used successfully to detect defects in fabrics by Jasper and Potapalli (1995) and Conci and Proença (2000a, 2000b). Both the works used Sobel edge detection to detect fabric defects and compared the results with those based on thresholding and fractal dimension.

Lane (1998) has detailed a systematic approach to detect fabric defect. Abidi *et al.* (1999) proposed an approach for the characterization of low resolution web surface using facet model. These approaches using edge detection are suitable for plain weave fabrics imaged at low resolution

Edge detection is a traditional technique used during image analysis. The amount of gray level transitions in the fabric images can represent lines, edges, point defects and other spatial discontinuities. Thus, these features have been largely used for testing, inspection and defect detection. It is more suitable for plain weave fabric images at low resolution. According to Unser and Ade (1984), the difficulty in isolating fabric defects with the noise generated from the fabric structure results in high false alarm rate and therefore usage of edge detection based approaches are less attractive.

Correlation is another method used for locating features in one image that appear in another and thus, provides a direct and accurate measure of similarity between two images. Any significant variation in the values of resulting measure indicates the presence of a defect. Bodnarova *et al.* (1998) have used the correlation coefficient from multiple templates to generate a correlation map for defect reporting. The correlation approach by Bennamoun and Bodnarova (1998) yields satisfactory results when detecting imperfections in regularly textured backgrounds. On the other hand, randomly textured backgrounds do not correlate well and demonstrate a limitation of this approach.

The use of gray level thresholding also enables to detect high contrast defects. The occurrence of a defect causes the signal level to rise or fall locally; the presence of a peak or trough then indicates a defect. This defect is detected when the signal crosses a decision threshold. This idea is used to detect fabric defects on moving textile web by Norton-Wayne *et al.* (1992, 1993). The defect detection can be effective even when web is covered by a fine and complex pattern.

Cho *et al.* (2005) proposed algorithm for finding defect in textile fabrics with fine web surface which shows 80% recognition rate on warp and pick float. The fabric inspection system that uses thresholding, proposed by Stojanovic *et al.* (2001), gives high detection rate with good localization accuracy and low rate of false alarm.

Costa *et al.* (2000) proved that pattern matching is the most difficult part for the traditional image subtraction method on patterned fabric inspection. Thomas and Cattoen (1994) proposed to use the image block densitometric profile to analyze the mean value of every row or column in the test image for defect detection. This profile analysis method was evaluated with simulated images and the results showed that the method will perform well for simple fabric patterns only.

Histogram and the rank function provide exactly the same information. De Natale (1986) has used rank order functions for the detection of artificially introduced defect in some Brodatz textures (Brodatz, 1956). Kauppines (2000) detailed the parquet slab grading using cumulative histogram. The colour information in textured images can also be used to extract colour histograms and this has been used by Boukouvalas *et al.* (1999) and Bergsa *et al.* (2000) to detect defects.

Huang *et al.* (2000) and Huang and Liu (2001) introduced the image processing technique, called gray projection curve, to recognize the fabric weave pattern and measure the yarn twist angle. They computed the gray projection curves by cumulating the gray values along both the horizontal and vertical directions. Hence, the yarn position and the corresponding interlaced points can be determined. Finally, the types of interlaced points can be estimated by analyzing the geometrical characteristics of yarns.

Pan and Gao (2008), Pan *et al.* (2008) and Pan *et al.* (2010b) employed a scanner to get the high resolution fabric image by scanning along the vertical direction and put forward a specific image size to analyze the fabric image. Locating the yarn clearances was used to correctly rectify the skew of the complete fabric image. Then, the position of the yarn clearances in the processed image can be estimated by the brightness information and the projection curve of the reflect image from the fabric surface. Finally, the accurate average distance of the yarn clearance can be computed by checking the distance of the yarn

clearances in turn and the fabric density can be calculated accordingly. It was reported that the proposed system showed a relative error of 7%.

Another novel technique was designed by Xie and Yu (2008) to digitize its image after the fabric sample was fixed using the mechanical alignment, the distortion can be eliminated to improve the accuracy of yarn density measurement and weave pattern recognition. It was reported that the error was less than 2% compared with manual testing results.

2.5. COMPARATIVE STUDIES

There are several comparative studies in the literature that evaluate texture analysis methods in applications to fabric defect detection. Each of these studies used different datasets and different parameter settings. Also resolution of the acquired images is an important factor in selecting the suitability of an approach for the defect detection.

Ozdemir *et al.* (1998) compared six texture features, consisting of MRF, 2D lattice filters, KLT, Co-occurrence matrices Laws filters and a FFT-based method, for detecting textile defects. For each method, the effects of various parameters have been examined and the experimental results concluded that, although many of the methods gave promising results, texture modeling using the 9th order Markov Random Field model gave the best results. Also, by considering the results obtained with respect to speed and reliability, MRF approach seems feasible for a real-time factory implementation.

Also, Bodnarova *et al.* (2002) have concluded that the optimal Gabor filters (optimized to detect five types of defects) perform better than gray level co-occurrence matrix, correlation or FFT based approaches. However this comparison is very limited on a set of 25 images and the information about the image resolution is also missing.

Tin Chi (2004), compares the performance of three methods which utilize matched masks, wavelet transform and neural network for fabric defect

detection. An evaluation of the performance of the methods was conducted on eight classes of fabric defects. In the first method, a multichannel filtering bank equipped with five matched mask was used. Matched masks are 2-D filters that characterize specific texture properties. Using this method, 96% of fabric defects were successfully detected and the false alarm rate was 6%.

The second method employed wavelet transform to decompose fabric images into multiscales and orientations. During the training stage, the parameters to be optimized include the rotation angles and the two thresholds applied on the horizontal and vertical transformed images. Using this method, only 76% of fabric defects were identified and the false alarm rate was 7%.

The last method took advantage of the fault tolerance and learning ability of neural networks. They explored the texture structure of defect-free images so that feature extraction was conducted on repeating units with proper selection of locations. For defect images, similar feature vectors were extracted and passed to the neural network. Using this method, the detection rate was as high as 92% and the false alarm rate was 6%. They further concluded that, the method employing matched masks proved the most effective in detecting fabric defects. The neural network method was next best. The wavelet transform method was the least effective, because it was only able to detect effectively certain classes of fabric defects.

Comparative studies performed by Randen *et al.* (1999, 1994) and Chen *et al.* (1999) indicate that the Gabor features in most of the cases outperform the other methods regarding the complexity and overall error rate. But the Gabor features suffer from a number of difficulties. A major difficulty of this method is to determine the number of Gabor channels at the same radial frequency and the size of the Gabor filter window in the application. Although a solid conclusion cannot be drawn to determine the best method for defect detection, it is clearly evident that filtering approaches, in particular Gabor filtering has been more popularly applied in these areas.

The texture inspection approach by Chetverikov and Henbury (2002) using the measure of structural regularity and texture anisotropy gives quite convincing experimental results. Therefore, a combination of these two approaches can offer the best performance for textile web inspection and is suggested for future investigation and comparison.

2.6. FINDINGS OF THE LITERATURE STUDY

The methods (both motif and non-motif based) reviewed in this chapter, can be divided into seven major categories, namely, statistical, spectral, model-based, structural, learning-based, hybrid and motif-based methods. The statistical group consists of techniques like auto-correlation, co-occurrence, morphology and fractal analysis-based methods. The spectral categories include techniques like Fourier, Gabor and wavelets. The model-based approaches include autoregressive models and Markov Random Field algorithms.

The structural category includes template-based and statistical and spectral-based techniques. The learning-based algorithm includes classification (neural network) and clustering algorithms. The hybrid models use techniques like NIR Imaging, Traditional Image Subtraction, Hash Function, Co-occurrence Matrix, Wavelet-preprocessed Golden Image Subtraction, Direct Thresholding, Bollinger Bands, Local Binary Patterns, Regular Bands. The motif based techniques use variance and energy of moving subtraction techniques for fault identification. The merits and demerits of each of these categories are presented respectively in Tables 2.1 to 2.5.

TABLE 2.1

MERITS AND DEMERITS OF STATISTICAL APPROACHES

METHOD	ADVANTAGES	DISADVANTAGES
Auto-correlation function	<ul style="list-style-type: none">• Suitable for yarn location in repetitive unit.• Suitable for the regularity analysis of the texture unit.	<ul style="list-style-type: none">• Difficult to analyze fabrics with irregular texture.
Morphological operations	<ul style="list-style-type: none">• Good description of texture and shapes.	<ul style="list-style-type: none">• Difficult to recognize weave patterns of fabrics with complex patterns or high density.
Co-occurrence matrix	<ul style="list-style-type: none">• Characterize the spatial relationship of pixels.• Describe texture information.	<ul style="list-style-type: none">• Complex computing process and cost, with low speed.• Some valuable information lost in the undirected distance.
Fractals (Spatial)	<ul style="list-style-type: none">• Provides multiresolution analysis and has a good localizing feature.• Defect detection is computationally simple.• Tunes itself to various geometry of defect and fabric images.	<ul style="list-style-type: none">• Does not cover all possible fractal dimensions.• High false alarm rate.

TABLE 2.2**MERITS AND DEMERITS OF SPECTRAL APPROACHES**

METHOD	ADVANTAGES	DISADVANTAGES
Fourier	<ul style="list-style-type: none"> • Employ frequency domain to characterize periodic structure. • Frequency spectrum is invariant to rescaling, translation and rotation. 	<ul style="list-style-type: none"> • Information in spatial domain is lost. • Types of interlacing points cannot be determined in specified region. • Not suitable for multicolored and textured fabrics.
Wavelet	<ul style="list-style-type: none"> • Provide multi-resolution of image. • Enable to focus on local details. • Obtain the horizontal and vertical sub-images. 	<ul style="list-style-type: none"> • The computation cost is high. • Not suitable for multicolored and textured fabrics.
Gabor	<ul style="list-style-type: none"> • Robustness, global optimality and extensive applicability. 	<ul style="list-style-type: none"> • Need large dataset for reliable results.

TABLE 2.3**MERITS AND DEMERITS OF MODEL-BASED APPROACHES**

METHOD	ADVANTAGES	DISADVANTAGES
Auto-Regressive Models	<ul style="list-style-type: none"> • Locate the wraps and wefts accurately. • Divide the fabric image into regular regions. 	<ul style="list-style-type: none"> • Cannot recognize the weave pattern of fabrics with high density exactly.
Markov Random Fields	<ul style="list-style-type: none"> • Isotropic behavior. • Only local dependencies. 	<ul style="list-style-type: none"> • Computing probability is complex. • Parameter estimation is difficult.

TABLE 2.4

MERITS AND DEMERITS OF STRUCTURAL AND LEARNING-BASED APPROACHES

METHOD	ADVANTAGES	DISADVANTAGES
Structural Approaches		
Structural	<ul style="list-style-type: none"> • Easy to extract texture. • Difficulty in handling stochastic variations in fabric structure. 	<ul style="list-style-type: none"> • Performs well on regular textures only.
Learning Based Approaches		
METHOD	ADVANTAGES	DISADVANTAGES
Neural Network	<ul style="list-style-type: none"> • Enable to give reasonable output. • Has a good fault tolerance and flexibility. 	<ul style="list-style-type: none"> • Needs large number of training features.
Clustering	<ul style="list-style-type: none"> • Suitable for unsupervised classification. 	<ul style="list-style-type: none"> • Not easy to determine initial clustering centers.

TABLE 2.5

MERITS AND DEMERITS OF HYBRID AND MOTIF-BASED APPROACHES

Hybrid Approaches		
Hybrid	<ul style="list-style-type: none"> • Combines merits of two or more models. 	<ul style="list-style-type: none"> • Computational complexities.
Motif-Based Approaches		
Motif-based	<ul style="list-style-type: none"> • Energy and Variance calculations are performed only within one lattice. • Invariant to slight distortion and misalignment. 	<ul style="list-style-type: none"> • Spatial relationships between pixels are weak.

The techniques reviewed in this chapter, can further be grouped as frequency-based or domain-based techniques (Zhang *et al.*, 2013). Analysis of the merits and demerits reveals that the frequency domain analysis-based methods seems to be difficult to recognize the weave pattern of derivative weaves, jacquard organizations or yarn dyed fabrics, though it is suitable for the recognition of fabrics which have a regular texture. Hence, further research is required to utilize the spatial domain-based methods, convenient for the yarn locating and weave pattern recognition. In summary, both the spatial domain-based methods and frequency domain-based methods have its advantages and disadvantages, and methods that helps to achieve high robustness algorithms are required.

For textile enterprises, effective fabric defect detection is an important guarantee to increase product margins, improve product quality, enhance product's international competitiveness and lower production costs. As the existing defect detection systems are costly both in terms of resources and cost along with other shortcomings such as detection inefficiency and poor test results (as presented in the above tables), improving the process of automatic defect detection for patterned fabrics is the focus of current research. The research methodology used is described in Chapter 3, Methodology.